An Analysis of Time-Based Pricing in Retail Electricity Markets

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Problem Definition: We empirically evaluate the short-term effects of time-based tariffs on the electricity demand, consumer welfare, retailers and the environment.

Academic / Practical Relevance: Electricity retailers around the world have been introducing time-based pricing programs. We study the short-term impact of such tariffs empirically.

Methodology: We build a structural estimation model of household electricity demand and analyze a data set from an Irish field experiment, consisting of the half-hourly electricity consumption of over three thousand households, combined with the wholesale price, system load and generation data. Using the estimates from the structural model, we conduct a counterfactual study to explore various questions of practical importance.

Results: Our empirical analysis reveals that focusing on the peak-load reduction metric, one can design a flexible time-of-use (TOU) tariff that is simple and predictable yet performs as well as real-time pricing (RTP) given a fixed time horizon for evaluation. The annual electricity bills of consumers decrease only slightly when they switch from the flat rate to time-based tariffs, but there can be significant volatility in month to month bills under time-based tariffs. In contrast, the more flexible a tariff in terms of pricing, the less volatility it creates in retailer’s profits throughout the year. Finally, switching from the flat rate to time-based tariffs would not change CO$_2$ emissions from electricity generation in Ireland significantly.

Managerial Implications: We find that time-based tariffs are effective in peak load reduction. However, the most appropriate time-based tariff depends on the context. If the goal is mitigating demand spikes over very short time spans, e.g. hours, then RTP is the most effective one. If the performance-relevant time horizon is longer, e.g. a month or a season, then a carefully designed TOU tariff with pre-determined rates can be just as effective as RTP. Consumers and retailers are largely unaffected by time-based tariffs which suggests that their adoption may be harder under opt-in policies, compared to opt-out policies. From an environmental perspective, our result that CO$_2$ emissions do not increase facilitates the adoption of time-based tariffs.

History: Edited on June 14, 2018.

1. Introduction

Electric utilities recently enjoyed access to rich data about their residential customers due to the widespread adoption of smart meters. In the European Union, Member States have committed to rolling out almost 200 million smart meters by 2020 (European Commission 2014). As of 2015, 57.1
million residential customers had advanced metering infrastructure (AMI) installations in the U.S. (U.S. Energy Information Administration (EIA) 2016), which accounts for 43.3% of all residential customers (EIA 2016, Table 10.10).

An AMI installation includes smart meters which measure and record electricity usage every hour at a minimum and provide the data to both the utility and the customers at least daily (EIA 2016). Therefore, customers with smart meters can make more informed decisions regarding the timing as well as the quantity of their consumption. The electric utilities can modify consumer demand through demand side management (DSM) programs offering financial incentives or education inducing behavioral change. Federal Energy Regulatory Commission (FERC) (2009) estimates that 60% of the DSM programs’ benefits will be due to time-based pricing strategies, whereby the utilities may vary the electricity price depending on the time of the day in order to encourage their customers to shift their demand from peak to off-peak hours. In the long term, the flattening of the demand curve during the day could allow cost-efficient base-load power plants to provide more electricity, and reduce the need for peak-load generation capacity. In the short term, the flattened demand curve can ensure improved utilization of the power plants, increased reliability, reduced cycling costs for the power plants and congestion charges for the network.

In this paper, we focus on the short-term effects of demand flattening and investigate which time-based tariffs are the most effective in reducing the peak load. The policymakers promote such time-based tariffs on the basis that it would benefit the consumers whereas the retailers will only consider implementing these changes if it is profitable for them. Thus, we also explore the impact of time-based tariffs on the consumers and retailers. Finally, demand flattening might lead to the unintended consequence of increasing carbon dioxide (CO$_2$) emissions. This increase may result from the difference in the carbon footprints of the base and peak load power plants. Therefore, we analyze how the flattened demand curve might affect CO$_2$ emissions.

To answer these questions, we use a data set consisting of the half-hourly electricity consumption and survey data of over three thousand households, collected during a field experiment in Ireland. The field experiment involves several time-of-use (TOU) tariffs, whereby the electricity price per kilowatt-hour (kWh) is set ahead of time but depends on the time of the day. These tariffs are tested on different subgroups of households; and demographic characteristics of these households are collected using surveys.

To conduct an empirical study on the aforementioned research questions, we build a structural estimation model. Our model and its analysis are conceptually similar to the empirical analysis in Hendel and Nevo (2013). We formulate the household demand model assuming utility maximizing agents, and estimate its structural parameters. Our counterfactual study characterizes the optimal retail electricity prices under the flat rate, TOU as well as real-time pricing (RTP) schemes using
data on the hourly system load and wholesale electricity market prices\(^1\). We do so for the perfect competition setting and the social planner setting, which corresponds to a regulated market\(^2\).

Our empirical analysis reveals several insights. First, focusing on the peak-load reduction metric, our results suggest that one can design a flexible TOU tariff that is simple and predictable, yet performs as well as RTP given a fixed time horizon for evaluation and comparison. For example, we show that an annual TOU tariff, where the electricity prices set for different hours of the day remain the same throughout the year, can lower the peak load as much as the RTP over a year. At the same time, the annual TOU tariff is not as effective as the RTP over each season. However, we also show that a seasonal TOU tariff, where the electricity prices set for different hours of the day can change in each season, can perform as well as the RTP over each season. On the one hand, the RTP provides a means of more granular pricing, because the prices can change every hour. So it is not surprising that it can do better than other tariffs. Indeed Hogan (2014) argues that the TOU tariffs can only capture a small part of the efficiency gain of RTP. On the other hand, the insight that a carefully designed flexible TOU tariff, e.g. seasonal TOU tariff, can do as well as RTP is surprising. We show this both for the social planner and perfect competition settings, see Section 6.1. The equivalence is shown analytically in the social planner setting, although the magnitude of the peak load reduction is an empirical finding. Unfortunately, we are not able to prove any analytical results for the perfect competition setting. However, our empirical findings support the same insight; see Table 5. Moreover, similar results carry over to other performance metrics such as off-peak and total consumption.

To repeat, the insight we glean from this analysis is that given a performance metric and the relevant time horizon for evaluation, e.g. a year, a season, a week, etc., one can design a TOU tariff (with pre-determined rates) that performs as well as RTP.

Second, in our analysis of the Ireland data, the equilibrium peak-to-off peak ratios (in our counterfactual study) turn out to be around, or less than two, leading to relatively modest percentage load reductions (see Tables 5, 6). However, it is often of interest to explore the impact of larger peak-to-off peak price ratios. For example, Federal Energy Regulatory Commission (FERC) (2009, pg. 61) considers peak-to-off peak price ratios of up to 8-to-1. Therefore, we consider the impact of varying this price ratio beyond two. Table 7 shows that this could result in a significant peak load reduction (by up to 5.7%), but it can also increase the total consumption (by up to 1.7%).

Third, we explore the impact of time-based tariffs on consumers’ electricity bills and retailers’ profit. We find that the annual electricity bills do not really change, but the time-based tariffs

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1 The real-time prices reflect the hourly fluctuations in the wholesale electricity market.

2 Note that the monopolistic setting results in the same optimal variable rates as the social planner’s but a much higher fixed fee.
can cause significant variation in electricity bills from month to month. Interestingly, the retailer’s profit becomes less volatile under time-based tariffs, whereas they exhibit more variation from month to month under the flat rate tariff.

Finally, we explore the potential impact of time-based tariffs on CO\textsubscript{2} emissions. One might expect that keeping the total consumption the same, time-based tariffs may increase CO\textsubscript{2} emissions because a flattened demand curve may lead the base-load power plants (which may be “dirtier”) to supply more and the “greener” plants to supply less. Interestingly, our results show that the CO\textsubscript{2} emissions do not increase under time-based tariffs, making it easier to adopt them from an environmental perspective.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature. In Section 3, we describe the consumer’s utility maximization problem, the social planner’s problem and the pricing problem in a perfectly competitive market. Our data set is described in Section 4, followed by the estimation results in Section 5. Section 6 conducts various counterfactual studies. We conclude in Section 7. Appendices A through EC.5 provide various further details of our data set, methodology and robustness checks.

2. Literature Review
The energy economics literature includes many papers focusing on the impact of time-based pricing strategies on electricity markets. On the theory side, Borenstein and Holland (2005) study a competitive retail electricity market, where only a fraction of the consumers are on RTP, and the rest is on uniform flat rate tariffs. They find that the competitive equilibrium will not be efficient unless all consumers face RTP. Their simulation results suggest that increasing the fraction of customers on RTP decreases the equilibrium capacity and increases consumer welfare in the long run. Joskow and Tirole (2006) extend Borenstein and Holland (2005)’s model, and consider heterogeneous consumers, demand rationing, and consumers that have real-time meters but are partially responsive to RTP due to transaction costs\textsuperscript{3}. They find that the competitive retail market can achieve an efficient equilibrium outcome under two-part tariff designs, and argue that the restriction of linear pricing may be deriving the inefficient equilibrium results in Borenstein and Holland (2005). Following Joskow and Tirole (2006), we also use two-part tariff structures, which also reflect the tariffs in Ireland.

On the empirical side, earlier studies on the residential demand side programs mostly use aggregate data, mainly monthly total consumption across designated peak and off-peak periods (Hausmann et al. 1979, Lawrence and Braithwait 1979, Caves and Christensen 1980, Caves et al. 1987, Wolak (2011) argues against the existence of a transaction cost associated with demand response, by analyzing the results from a dynamic pricing experiment.

\textsuperscript{3}Wolak (2011) argues against the existence of a transaction cost associated with demand response, by analyzing the results from a dynamic pricing experiment.
Herriges and King 1994, Reiss and White 2005), and cover a wide array of functional forms for their utility maximizing agents. Lawrence and Braithwait (1979) use the linear expenditure system as their demand model, where Haussmann et al. (1979), Reiss and White (2005) estimate linear demand equations. Caves and Christensen (1980) compare three models for consumer utility; the CES model, the Translog model and the Generalized Leontief (GL) model. Herriges and King (1994) construct a double log demand function under time varying rates and the short-run elasticities. All of these models have trade-offs in terms of flexibility, computational complexity and identification due to having a large number of parameters. Our dataset contains individual household level data, recording hourly consumption for many households, with relatively less variation in prices charged to consumers. Therefore, we find that the linear model works best for our dataset in terms of balancing identification strength, prediction accuracy and computational ease.

Allcott (2011) also uses a linear demand model, and estimates demand elasticities for residential customers on hourly varying real-time prices, using data for about 700 households, tracked for 8 months for a RTP experiment in Chicago. The households in Allcott (2011)’s dataset are voluntary participants of an earlier energy-efficient air conditioner (AC) replacement initiative, and had access to automated temperature control via programmable thermostats. Allcott’s estimations from hourly consumption data show that households are price elastic. They respond to peak prices by reducing peak consumption, and their off-peak consumption do not increase, which is directionally similar to our findings. Allcott (2011) also investigates the average consumer surplus from real-time pricing, with the simplifying assumption that the retail prices are fixed, and finds that consumers save 2.7% of their energy bill from moving on to RTP, which might be due to the overall energy conservation from using programmable and energy-efficient AC units. We also observe a decrease in annual electricity bills of consumers switching to time-based prices, but at less than 1%. Finally, Allcott (2011) finds that carbon emissions slightly decrease under RTP, by multiplying the emissions rate of the marginal generator with the quantity demanded under comparable prices.

Holland and Mansur (2008) also study the environmental effects of RTP, and assuming RTP flattens demand, they estimate the impact of demand flattening on various greenhouse gas emissions. Keeping the average daily load constant (but varying the load over the day), they show that the impact of demand flattening differs across regions, based on their dispatch mix. We also study the change in emissions, but under the optimal retail prices, and by using the empirical distribution of actual dispatch decisions from each generator in the market. In the Ireland market, marginal emissions rate is relatively constant between peak and off-peak periods. Thus, we find no significant impact of demand flattening on CO₂ emissions.

Our empirical findings on welfare effects are consistent with the simulation study of Holland and Mansur (2006) which investigates the effects of RTP adoption in the short-run and find welfare
gains to be 0.24% of consumer’s energy bills. Both our paper and Holland and Mansur (2006) assume that the generating capacity is fixed in the short term. Holland and Mansur (2006) suggest that the significant portion of the potential welfare benefits of RTP adoption comes from avoiding the construction of generating capacity, hence, the difference between the long-term and the short-term welfare gains. On the other hand, Borenstein (2005) focuses on the long-run efficiency gains from RTP under competitive generation and retail electricity markets. Calibrating the model with actual demand and production costs from U.S. markets, Borenstein uses simulations to find the amount of each type of capacity that would be built in the long-run competitive equilibrium. Results show that RTP substantially reduces the use of peaker generation, and the long-run efficiency gains from RTP can be significant. A simple TOU tariff can only capture a small share of these efficiency gains in his study. The crucial feature of Borenstein’s analysis of long-term effects is that the level of capacity investments are allowed to change and the resulting savings are passed onto the consumers. More recently, in the operations management literature, Kok et al. (2015) model the impact of flat and peak-load pricing on the capacity portfolio (conventional, solar and wind energy investments) for an electricity utility with an existing fleet of conventional generators. They also explore implications of these investments on carbon emissions and consumer surplus, and study the effectiveness of subsidies for renewable investments and taxes on emissions. Lastly, they perform a numerical study to illustrate some of their results on the aggregate demand, wind and conventional energy output data for Texas, and the solar energy output generated by a simulation study. Assuming a peak period of 12 hours and the total demand remains the same in a day, they perform a sensitivity analysis by lowering peak consumption by 5, 10 or 15%. Our work complements these papers as we focus on the short-run effects of the time-based pricing. Moreover, given the empirical nature of our study, we can derive sharper conclusions by focusing specifically on the Irish market and analyzing observed consumer behavior.

Two other studies analyze the same dataset as in our paper. Di Cosmo et al. (2014) uses a differences-in-differences approach to look at the effects of information stimuli on household demand. Based on their analysis, they conclude an in-house display providing regular feedback about the quantity and cost of electricity consumed is more effective in reducing peak-period consumption than other stimuli, and this effect becomes stronger as the ratio of peak to off-peak prices increases. However, they run their regressions on disjoint groups of households under different information treatments which prevents them from observing the effect of pricing, or the combination of pricing and information stimuli together. In our model, we account for the effect of in-house display on consumption but mainly investigate the impact of pricing on consumption decisions. Again focusing on the information stimuli, Carroll et al. (2014) investigate the effects of information on a household’s knowledge about their own electricity consumption. They find that
information effects have a significant effect on household’s knowledge but more knowledge does not necessarily affect the consumption decisions.

In terms of methodology, this paper belongs to the literature on structural models of consumer behavior. A notable example in this literature is Hendel and Nevo (2013), which investigates intertemporal price discrimination in storable goods markets through a structural estimation model. Similar to Hendel and Nevo (2013), we assume that the observed demand is the optimal solution to the consumers’ utility-maximization problem\(^4\), with the addition of a simple econometric error term to capture the variations in the data. As in Hendel and Nevo (2013), we estimate the parameters of the consumer’s demand model by comparing the observed consumer behavior to the one predicted by the model. Also similar to Hendel and Nevo (2013), we characterize the optimal pricing decisions of the sellers in response to the consumers’ demand model, and investigate the counterfactual implications of the pricing decisions on consumer behavior and welfare. Additionally, we also study the counterfactual implications of various time-based pricing schemes on the environment.

The following section describes the consumers’ and the retailers’ decision making problems.

3. The Model

This section lays the groundwork for our structural estimation approach, which closely follows the empirical analysis of Hendel and Nevo (2013). We first introduce the consumer’s utility maximization problem. Next, we discuss the social planner’s problem as well as the equilibrium prices in a perfectly competitive market, which facilitate the counterfactual study undertaken in Section 6.

In the consumer’s utility maximization model, each household \(n\) chooses its electricity consumption, \(x^n\), and the quantity of a numeraire good\(^5\), \(x^n_0\), to maximize its utility from the consumption of these goods, \(U^n(x^n_0, x^n)\), such that the total expenditure of the household does not exceed its budget \(Y^n\):

\[
\begin{align*}
\max_{(x^n_0, x^n)} & \quad U^n(x^n_0, x^n) = x^n_0 + u^n(x^n) \\
\text{subject to} & \quad x^n_0 + \sum_d \sum_t p_{dt} x^n_{dt} \leq Y^n,
\end{align*}
\]

where the electricity consumption and price vectors, \(x^n = (x^n_d)\) and \(p = (p_{dt})\), are defined over the planning horizon, that is, over days \(d \in \{1, \ldots, D\}\) and hours of the day \(t \in \{1, \ldots, T\}\). Finally, \(u^n(x^n)\) denotes the utility of household \(n\) from electricity consumption over the planning horizon\(^6\).

\(^4\)We choose a quadratic utility function, and end-up with a linear demand equation whereas Hendel and Nevo (2013) choose to work with a log-linear demand model.

\(^5\)The numeraire good is a proxy for all goods other than electricity.

\(^6\)We assume the consumption of electricity is separable from the consumption of other commodities for residential consumers (see Appendix D of Electric Power Research Institute (EPRI) 2013). Furthermore, we assume that the utility function, \(U^n(x^n_0, x^n)\), is quasilinear in the numeraire good \(x^n_0\) as in Hendel and Nevo (2013) and Allcott (2011), and therefore can be written as \(x^n_0 + u^n(x^n)\). Electricity consumption is a small part of the household’s budget, and the quasilinearity assumption ensures that the electricity consumption decision does not depend on the budget \(Y^n\).
We denote the solution of the utility maximization problem (1) by $x_{dt}^n(p)$ for household $n$, day $d$ and hour $t$. To facilitate our empirical analysis in Section 5, we will assume a specific functional form for the utility function $u^n(x^n)$ and hence, for the demand model $x_{dt}^n(p)$.

Next, we discuss the social planner’s pricing problem and the equilibrium prices in a perfectly competitive market, which facilitate the counterfactual study undertaken in Section 6. In these models below, the social planner and the retailers buy electricity at the wholesale price $w_{dt}$ on day $d$, at hour $t$, and then sell it to the end users. We also assume that neither the social planner, nor the retailers can fully observe the consumers’ environment. To be specific, we assume that the social planner and the retailers face households with hourly demand $q_{dt}^n$ where the hourly demand includes an i.i.d. shock with zero mean, $\epsilon_{dt}^n$, such that $q_{dt}^n = x_{dt}^n + \epsilon_{dt}^n$. However, the retailers and the social planner cannot observe $\epsilon_{dt}^n$ at the time of setting prices. Therefore, following Hendel and Nevo (2013, see pages 2732 and 2736-37), we assume that the social planner and the retailers work with only the demand model $x_{dt}^n(p)$ while choosing the optimal tariffs.

Following Joskow and Tirole (2006), we then formulate the social planner’s problem as follows: The social planner chooses the optimal two-part tariff with a variable price $p_{dt}^*$ and a fixed fee $A^*$ to maximize the consumers’ net surplus such that the retailers cover the costs of providing electricity. Formally, the social planner’s problem is formulated as below and its solution is provided in Appendix EC.1.1 under different time-based tariffs:

$$\max_{(p,A)} \sum_n \left( u^n(x^n) - \sum_d \sum_t p_{dt} x_{dt}^n \right) - AN$$

subject to

$$AN + \sum_n \sum_d \sum_t p_{dt} x_{dt}^n \geq \sum_n \sum_d \sum_t w_{dt} x_{dt}^n. \ (2)$$

Note that a monopolist retailer would maximize its own profit subject to the constraint that the consumers’ net surplus is greater than or equal to zero. It is easy to see that the monopolist would charge the same unit rates $p^*$, as those in the solution to the social planner’s problem in (2), but would extract all of the consumer surplus through a higher subscription fee $A$.

We determine the equilibrium under perfect competition by setting the retailer’s profit to zero. To facilitate the comparison with the social planner’s problem, we assume that retailers recover part of their costs through a fixed fee, which we set equal to the fixed fee in the social planner’s problem. The retailers recover the rest of their costs through variable rates. The analysis of the perfectly competitive equilibrium under different time-based tariffs is straightforward and is provided in Appendix EC.1.2.

7 We assume that wholesale prices are exogenous with respect to the pricing problem. We have also formulated the wholesale price as load-dependent, and found that our findings are directionally robust to this assumption. See Appendix EC.4.

4. Data

Our consumer data includes the electricity consumption and survey data of 3390 households collected by the Commission for Energy Regulation (CER), the independent regulator of electricity and natural gas sectors in Ireland, through the Smart Metering Electricity Customer Behavior Trials (CER 2011). The electricity consumption data of all participant homes was recorded in 30-minute intervals through two periods: the benchmark period and the test period. The benchmark period lasted from July 14, 2009 to December 31, 2009, during which all participants were charged a flat rate of 14.1 cents/kWh (in 2009 Euros). The test period was from January 1st, 2010 to December 31st 2010, during which several TOU tariffs and DSM stimuli were tested. There are five test groups in the dataset: groups A, B, C and D, which pay a flat rate during the benchmark period and a TOU tariff during the test period; group E, which is the control group paying the flat rate of 14.1 cents per kWh during both the benchmark and the test periods. The distribution of households into tariff groups and their respective TOU tariffs are given in Table 1.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>The distribution of households into tariff groups and their respective TOU tariffs</th>
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<tbody>
<tr>
<td></td>
<td>Weekday Prices (c/kWh)</td>
</tr>
<tr>
<td></td>
<td>Group</td>
</tr>
<tr>
<td>---------</td>
<td>-------</td>
</tr>
<tr>
<td>A</td>
<td>938</td>
</tr>
<tr>
<td>B</td>
<td>364</td>
</tr>
<tr>
<td>C</td>
<td>962</td>
</tr>
<tr>
<td>D</td>
<td>364</td>
</tr>
<tr>
<td>E</td>
<td>762</td>
</tr>
</tbody>
</table>

Figure 1 shows how the average weekday consumption changes over a day for control-group households in each of the three seasons: winter, summer and Christmas. The Christmas season corresponds to the month of December, the summer season corresponds to the months April through October, and the winter season corresponds to the rest of the year. The daily consumption profiles are drastically different over summer, winter and Christmas seasons, and the peak consumption in summer is significantly lower than that in Christmas.

The participants of the field experiment were also invited to take part in a telephone assisted survey about the demographic characteristics of their household, the ownership and use of electrical appliances, investments in energy efficiency and expectations from the trial. In our analysis, we only consider the households that participated in the survey, which is 83% of the field experiment.

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9 The design of the recruitment process and whether the sample is representative of the population are discussed in Appendix A.
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Figure 1 Average consumption pattern of a household in the control group during weekdays, across 2010, for three different seasons.

Weekday Consumption for Control Group Households

Note. The Christmas season corresponds to the month of December, the summer season corresponds to the months April through October, and the winter season corresponds to the rest of the year.

participants. More information on excluded households, and the representativity of the final sample are discussed in Appendix B.

We also use the hourly temperature data recorded at the Dublin International Airport to capture the temperature change during the day. Figure 2 shows the fluctuations in the daily averages of the temperature and the system load in 2010. The lower temperatures in winter and Christmas seasons lead to higher consumption of electricity especially due to space and water heating. On the other hand, electricity usage is not as high in the summer season because in EU-27 countries, the air conditioners are rare and account for only 2% of residential electricity consumption (Joint Research Centre 2009) as opposed to 18% in the U.S. (EIA 2014). As Ireland has a colder climate than the EU average, the air conditioner use in Ireland is even lower.

Figure 2 The fluctuations in the average daily temperature (°C), and the average daily system load (MWh) during the year 2010, in Ireland.
In our counterfactual study, the wholesale electricity prices are used in order to calculate the price in the retail electricity market. The wholesale price of electricity is the sum of the system marginal price (SMP), several other market operating charges and capacity payments. These cost parameters and the details of their calibration are described in Appendix C. Finally, we use the dispatch data for each generator unit in the Irish wholesale electricity market and the total system load for each hour in 2010 (SEMO 2014a). Section 6.3 provides a description of the portfolio of generators in Ireland and their corresponding emissions rates.

5. Estimation and Identification

To facilitate our empirical analysis, we assume that the utility function $u^n(x^n)$ in (1) is quadratic, which results in the following linear demand model:

$$ x_{dt}^n = \alpha_{dt}^n + \beta_{dt}^n p_{dt}^n + \sum_{|t-s| \leq 2} \theta_{t-s}(p_{ds}^n - p_{dt}^n), \tag{3} $$

where $n \in \{1, \ldots, 3390\}$ denotes the households in the field experiment, $d \in \{1, \ldots, 256\}$ represents the $d$th weekday of year 2010, and $t \in \{1, \ldots, 24\}$ represents the hours in day $d$.

The prices charged in the experiment are denoted by $p_{dt}^n$, and are in cents/kWh, in 2010 Euros. The consumption $x_{dt}^n$ is measured in Watt-hr (Wh). We assume that each hour’s own price sensitivity parameter is given by $\beta_{dt}^n = \beta_0 + \beta_1 \text{monitor}^n + \beta_2 \text{peak}_t + \beta_3 \text{day}_t$. Here, monitor$^n$ indicates the presence of an electricity monitor in household $n$; peak$^t$ and day$^t$ are indicator variables that show the pricing period of hour $t$ in the experiment. Likewise, the intercept parameter is modeled as $\alpha_{dt}^n = \alpha_0 + \alpha_{\text{adult}} \text{num adults}^n + \alpha_{\text{temp}} \text{temp}_{dt} + \alpha \cdot \tilde{Z}_{dt}$. Here, num adults$^n$ captures the number of adult occupants of household $n$ as a surrogate for the size of the home$^{12}$; temp$^t_{dt}$ denotes the temperature (in Celsius) for day $d$, hour $t$; $\tilde{Z}_{dt}$ includes the season and hour indicators for day $d$ and hour $t$.

The demand model incorporates consumption substitution as captured by the last term on the right-hand side of Equation (3). Namely, when choosing their consumption, consumers take into account the prices during the neighboring two hours and decide accordingly. This may result in shifting some of their consumption to those neighboring hours and vice versa. Specifically, the

$^{10}$The details of the utility function and the derivation of the resulting demand model in (3) are provided in Appendix D.

$^{11}$Weekends and public holidays are excluded from the analysis. The reason is that our analysis focuses on peak pricing and peak load reduction; however, weekends and holidays in the field experiment have no designated peak period or peak pricing. Therefore, we use the weekday data in our analysis. In order to disregard the substitution between weekdays and weekends, we assume the price of the last two hours on Sundays are identical to the price in the first two hours on the following Mondays, respectively. Similarly, the price of the first two hours on each Saturday is identical to the price in the last two hours of the previous Friday.

$^{12}$A detailed analysis (available from the authors) considered a number of alternatives. However, the number of adults appears to capture the impact of the household size on consumption the best.
consumption in hour $t$ increases (decreases) by $\theta_i$ watt-hours for each cent/kWh of higher (lower) price within $i$ hours before and after for $i \in \{1, 2\}$. Note that if there is no price difference between the current hour $t$ and the neighboring hour $s$, then there is no substitution. The choice of this particular demand substitution model is driven primarily by the identification and the fit of the model by/to the data; see Appendix E for further details.

As mentioned earlier, we let

$$q^n_{dt} = x^n_{dt} + \epsilon^n_{dt}$$  \hspace{1cm} (4)

denote the realized consumption where the errors $\epsilon^n_{dt}$ represent the unobserved components of consumer preferences, which are not correlated with the observed variables, are mean zero and i.i.d.

**Identification.** Mathematically, we can write Equation (3) in matrix notation as $x = Z\gamma + \epsilon$, where all parameters to be estimated are included in $\gamma$. It is straightforward but tedious to check that in our case $Z$ is of full column rank. Therefore, the parameters are given by the closed-form solution $\gamma = (Z^TZ)^{-1}Z^T x$, which exists because $Z$ is of full column rank. To elaborate further, consider the coefficient $\alpha_{\text{temp}}$ of the hourly temperature variable $\text{temp}_t$ ($\alpha_{\text{temp}}$ is an element of $\gamma$). Intuitively, there is enough variation in the hourly temperature that the corresponding column in $Z$ is linearly independent of all other columns. Thus, we can identify $\alpha_{\text{temp}}$. Clearly, if the temperature were constant throughout, we wouldn’t be able to identify $\alpha_{\text{temp}}$. Moreover, if the pattern of variation in temperature were identical to that in prices, we wouldn’t be able to identify $\alpha_{\text{temp}}$ and $\beta^n_{dt}$ separately.

<table>
<thead>
<tr>
<th>Table 2</th>
<th>The estimates for the demand parameters.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Coefficient</td>
</tr>
<tr>
<td># of adults ($\alpha_{\text{adult}}$)</td>
<td>197.5**</td>
</tr>
<tr>
<td>(Wh/adult)</td>
<td>(0.231)</td>
</tr>
<tr>
<td>Temperature ($\alpha_{\text{temp}}$)</td>
<td>-10.86***</td>
</tr>
<tr>
<td>(Wh/°C)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Price ($\beta_0$)</td>
<td>-9.7***</td>
</tr>
<tr>
<td>(Wh/cents)</td>
<td>(0.232)</td>
</tr>
<tr>
<td>Monitor × Price ($\beta_1$)</td>
<td>-2.62***</td>
</tr>
<tr>
<td>(Wh/cents)</td>
<td>(0.043)</td>
</tr>
<tr>
<td># of observations:</td>
<td>20.6m</td>
</tr>
</tbody>
</table>

The symbols ** and *** indicate significance levels at the 5% and 1%, respectively. Standard errors are given in parentheses. +We include the control variables for the seasons of the year and the hours of the day as given in $Z_{dt}$.

Table 2 shows the estimates of the coefficients, standard errors and the significance of the variables in the regression equation (4). All coefficients are significant at a significance level of 0.5% or 0.1%. The consumption decreases for every °C of increase in the temperature, consistent with the
Irish data in Figure 2. During night hours, households respond to every cent of price increase by reducing their usage by 9.7 Wh ($\beta_0$); the households reduce their consumption less for the peak and day periods as shown by the estimates of $\beta_2$ and $\beta_3$, respectively. On the other hand, having an electricity monitor at home makes the households more responsive to price changes as indicated by the estimate of $\beta_1$.

Table 2 does not show the coefficient estimates for the control variables that appear in the intercept parameter $\alpha_{dt}^{\beta}$, i.e., $\alpha_0 + \alpha \cdot \tilde{z}_{dt}$. We present the averages and the standard errors for these in Table 3. When averaged over the respective periods, the control variables have the lowest effect for summer, and the highest for Christmas, reflecting the seasonality in customer demand, cf. Figure 1. They are also lower during off-peak (day and night) hours, compared to peak hours.

### Table 3  
*Average values for $\alpha_0 + \alpha \cdot \tilde{z}_{dt}$ across seasons and pricing periods (Watt-hr).*

<table>
<thead>
<tr>
<th>Period</th>
<th>Average</th>
<th>Period</th>
<th>Average</th>
<th>Period</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Summer Night</td>
<td>351.9</td>
<td>Winter Night</td>
<td>328.8</td>
<td>Christmas Night</td>
<td>402.3</td>
</tr>
<tr>
<td></td>
<td>(2.84)</td>
<td></td>
<td>(2.8)</td>
<td></td>
<td>(3.02)</td>
</tr>
<tr>
<td>Summer Day</td>
<td>783.1</td>
<td>Winter Day</td>
<td>920.5</td>
<td>Christmas Day</td>
<td>1146.4</td>
</tr>
<tr>
<td></td>
<td>(8.97)</td>
<td></td>
<td>(8.95)</td>
<td></td>
<td>(8.99)</td>
</tr>
<tr>
<td>Summer Peak</td>
<td>1075.7</td>
<td>Winter Peak</td>
<td>1500.7</td>
<td>Christmas Peak</td>
<td>1902.5</td>
</tr>
<tr>
<td></td>
<td>(3.78)</td>
<td></td>
<td>(3.73)</td>
<td></td>
<td>(4.45)</td>
</tr>
</tbody>
</table>

The averages are over their respective periods. Pricing periods are as defined in Table 1. Standard errors are given in parentheses. All averages are significant at the 1% level.

6. **The Counterfactual Study**

Building on the demand model estimates of the previous section, this section conducts a counterfactual analysis that explores how the peak and total loads change under time-based tariffs compared to those under the flat-rate tariff. The counterfactual study also investigates how time-based tariffs affect the consumer’s electricity bills and retailers’ profits as well as the carbon dioxide emissions due to electricity generation.

The counterfactual study considers several tariffs motivated by the Irish electricity market: In the regulated Irish market, the utilities charged their residential customers a two-part tariff with a flat variable rate (hereafter, this tariff will be referred to as the “flat rate”) and a fixed charge. After the deregulation, a decision by the Ireland Commission for Energy Regulation mandated the use of a TOU tariff as the default tariff for the residential electricity consumers. The TOU tariff is also a two-part tariff comprising of variable and fixed rates where the per-unit rate changes during the day following a predetermined schedule (CER 2014). Currently, the retailers are also encouraged to experiment with more complex pricing structures such as RTP to explore the potential for the wide-spread application of such pricing schemes. Consequently, we consider the following three
types of pricing regimes in this section: The flat rate, the TOU tariff and the RTP. Under the flat rate, there is a constant variable rate, \( p_{dt} = p \), \( \forall d, t \); under the TOU tariff, there are \( M \) periods \( T_m, m = 1, \ldots, M \), and the retailer chooses the price, \( p_m \), for period \( T_m, m = 1, \ldots, M \), i.e., \( p_{dt} = p_m \) for all \( d, t \in T_m \). For these tariffs, a fixed fee of \( A \) can be charged in addition to the variable rates. Finally, under RTP, the retailer can choose a separate price \( p_{dt} \), for each day \( d \in \{1, \ldots, D\} \) and hour \( t \in \{1, \ldots, T\} \).

There is a significant seasonal difference in the consumption during peak times, as shown in Figure 1. The peak load during Christmas is closer to the electricity generation capacity than the peak load during summer. Therefore, reducing the peak load during Christmas can generate significant benefits in terms of increased utilization of base-load power plants, increased reliability and reduced cycling costs of power plants\(^{13}\). However, the load during summer peak times does not put pressure on the electricity generation capacity so reducing the load during these times can unnecessarily restrict the consumption of electricity and does not generate significant benefits for the system. Therefore, we also consider a more flexible TOU tariff called a “seasonal TOU tariff”, which can charge different day, night and peak rates for each season as opposed to the “annual TOU tariff” which charges the same day, night and peak rates throughout the year.

6.1. Equilibrium Retail Prices and Consumption

Using the estimates in Section 5, we compute the equilibrium retail prices for each of the aforementioned pricing schemes. Table 4 shows these prices under the social planner’s and perfectly competitive settings\(^{14}\). In the Christmas season, the peak-to-night ratio increases to slightly above two under both market settings (under the seasonal TOU tariff) due to the significantly higher demand and corresponding wholesale prices during Christmas peak hours. However, the peak-to-night price ratio under the optimal annual TOU tariff is less than two due to the relatively low variation in the wholesale prices in Ireland\(^{15}\).

Table 5 shows the percentage change in the peak, off-peak\(^{16}\) and total consumption when the households switch from the optimal flat-rate tariff to the optimal TOU tariffs or RTP. Under the social planner setting, the total consumption throughout a year is the same for all tariff structures: flat rate, annual TOU, seasonal TOU and RTP. Moreover, the peak and off-peak consumption

\(^{13}\) Cycling costs are associated with the operation of electric generating units at varying load levels, including on/off, load following, and minimum load operation, in response to changes in system load requirements (Kumar et al. 2012).

\(^{14}\) Recall that a monopolist retailer would charge the same unit rates \( p^* \) as the social planner, but would extract the remainder of the consumer surplus through a higher subscription fee \( A \).

\(^{15}\) In 2010, the average wholesale price was 18.9 cents per kWh for peak hours, and 13 cents per kWh for off-peak hours in Ireland.

\(^{16}\) Day and night periods in the data set are considered as the off-peak period.
Table 4 | Equilibrium retail prices.

<table>
<thead>
<tr>
<th></th>
<th>Social Planner</th>
<th>Perfect Competition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Night</td>
<td>Day</td>
</tr>
<tr>
<td>Flat Rate</td>
<td>12.5</td>
<td>12.5</td>
</tr>
<tr>
<td>Annual TOU</td>
<td>11.5</td>
<td>14.2</td>
</tr>
<tr>
<td>Seasonal TOU</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Summer</td>
<td>11.4</td>
<td>14.5</td>
</tr>
<tr>
<td>Winter</td>
<td>11.2</td>
<td>13.4</td>
</tr>
<tr>
<td>Christmas</td>
<td>13.7</td>
<td>15.8</td>
</tr>
<tr>
<td>RTP</td>
<td>$w_{dt}$</td>
<td>$w_{dt}$</td>
</tr>
</tbody>
</table>

Retail rates are in cents/kWh. The annual fixed fee $A$ for both market settings is €115 under flat rate, €17 under the annual TOU tariff, €11 under the seasonal TOU tariff, and €0 under RTP. Note that $w_{dt}$ denotes the wholesale electricity price on day $d$ and hour $t$.

Throughout a year is the same under annual and seasonal TOU tariffs as well as RTP. Proposition EC.3 in Appendix EC.2 shows that these results follow from the linear demand model and the social planner’s pricing problem formulation. As such they can be viewed as theoretical results. Nonetheless, the magnitudes of these changes are empirical findings.

Under perfect competition, in equilibrium, the real-time prices reflect the wholesale prices directly as in the social planner setting, as shown in Table 4. Similarly, the flat rate under perfect competition is the same as that in the social planner setting: Recall that under perfect competition, we chose the same fixed subscription fee as the optimal fixed fee under the social planner setting to make the prices under two settings comparable. This makes the perfect competition setting to be equivalent to the social planner setting under the flat-rate tariff, hence, the same equilibrium flat rate under both settings; see Proposition EC.4 in Appendix EC.2 for a proof of this.

However, we are not able to derive any further results or insights theoretically. As such, the rest (and the great majority) of our findings are empirical. For example, the peak, off-peak and total consumption under annual and TOU tariffs under perfect competition are slightly different from each other, as shown in Table 5. In particular, the annual TOU tariff, the least flexible of all time-based tariffs we consider, performs slightly better than the more flexible seasonal TOU tariff and the RTP in terms of the annual peak load reduction, which appears counterintuitive at first. To shed more light on this, Table 6 zooms in on the peak load reduction in each season and shows that the annual TOU tariff in fact reduces the summer peak load the most when it is least needed, i.e., when the demand is much lower than the generator capacity. However, the annual TOU tariff reduces the Christmas peak load the least, when the peak load reduction is the most valuable, as shown in Figure 1 and Table 6. The reason is that the annual TOU charges the same three-period tariff (day, night, peak) across different seasons. Therefore, it overcharges consumers during summer while it undercharges them in the Christmas season. On the other hand, the seasonal TOU tariff has the flexibility to charge different day, night and peak prices in different
seasons. This allows the seasonal TOU tariff to lower the peak load when it is most needed, i.e., in the Christmas season.

In a similar vein, the seasonal TOU tariff lowers the peak load in each season slightly more than the most flexible tariff, RTP, under perfect competition. However, when we focus on the hourly peak load reduction, the RTP performs better in terms of reducing the hourly demand spikes. In Figure 3, we zoom into 7 pm on December 22, 2010 when we observe the highest load under the flat-rate tariff in 2010. Clearly, the RTP achieves the highest peak load reduction during the demand spike. This is because the RTP has the flexibility to charge a high price during demand spikes while keeping the prices low elsewhere.

Table 5: The impact of optimal TOU tariffs and RTP on the peak, off-peak and total loads

<table>
<thead>
<tr>
<th></th>
<th>The Change in The Consumption: Peak</th>
<th>Off-Peak</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Social Planner</strong></td>
<td>Annual TOU -1.2%</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Seasonal TOU -1.2%</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>RTP -1.2%</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td><strong>Perfect Competition</strong></td>
<td>Annual TOU -1.4%</td>
<td>0.4%</td>
<td>0.1%</td>
</tr>
<tr>
<td></td>
<td>Seasonal TOU -1.3%</td>
<td>0.3%</td>
<td>0.1%</td>
</tr>
<tr>
<td></td>
<td>RTP -1.2%</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

The percentage change under the annual and seasonal TOU tariffs and RTP compared to the flat rate under the social planner and perfect competition settings.

Table 6: Comparison of seasonal peak load reduction under equilibrium prices.

<table>
<thead>
<tr>
<th>Peak Load Reduction:</th>
<th>Summer</th>
<th>Winter</th>
<th>Christmas</th>
<th>Annual</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Social Planner</strong></td>
<td>Annual TOU -1.5%</td>
<td>-1.1%</td>
<td>-0.8%</td>
<td>-1.2%</td>
</tr>
<tr>
<td></td>
<td>Seasonal TOU -0.7%</td>
<td>-1.3%</td>
<td>-2.4%</td>
<td>-1.2%</td>
</tr>
<tr>
<td></td>
<td>RTP -0.7%</td>
<td>-1.3%</td>
<td>-2.4%</td>
<td>-1.2%</td>
</tr>
<tr>
<td><strong>Perfect Competition</strong></td>
<td>Annual TOU -1.8%</td>
<td>-1.3%</td>
<td>-1.0%</td>
<td>-1.4%</td>
</tr>
<tr>
<td></td>
<td>Seasonal TOU -0.7%</td>
<td>-1.4%</td>
<td>-2.5%</td>
<td>-1.3%</td>
</tr>
<tr>
<td></td>
<td>RTP -0.7%</td>
<td>-1.3%</td>
<td>-2.4%</td>
<td>-1.2%</td>
</tr>
</tbody>
</table>

The change in peak load by season with annual TOU, seasonal TOU and RTP compared to the flat rate under the social planner versus the perfectly competitive setting.

In markets with higher variation, the optimal peak to off-peak price ratio can be significantly higher than what we observe in Table 4. Indeed, Federal Energy Regulatory Commission (FERC) (2009, pg. 61) considers a peak to off-peak price ratio of 8-to-1 in their assessment of the potential of demand response programs. Therefore, we also consider the impact of increasing the peak to off-peak price ratios on the peak and total consumption in Table 7, which holds for both market
Figure 3  The average hourly load profile during peak hours for December 22, 2010, under different price tariffs.

<table>
<thead>
<tr>
<th>Prices</th>
<th>Change in Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price Ratio</td>
<td>Peak</td>
</tr>
<tr>
<td>2</td>
<td>22.1</td>
</tr>
<tr>
<td>3</td>
<td>29.5</td>
</tr>
<tr>
<td>4</td>
<td>35.5</td>
</tr>
</tbody>
</table>

The flat rate and time-based prices are set such that the average weekly expenditure is the same under all tariffs compared to the flat rate given that the household don’t change its consumption. We use the optimal flat rate as a baseline tariff for this study, which is 12.5 cents/kWh under both social planner and perfectly competitive settings. We calculate the weekly expenditure of an average household under the flat rate, and determine the peak and off-peak prices corresponding to peak-to-off-peak ratios of two, three and four such that these prices result in the same weekly expenditure for the average household given that the household does not change its consumption under the TOU tariff. A similar assumption is made in the tariff design of the original field experiment such that the average participant who did not alter their electricity consumption pattern was not penalized financially under the time of use tariff (CER 2011, page 5).

Another way to compare the RTP and TOU rates is to measure how much of the variability in the real-time prices the TOU rates can capture. Given that TOU prices are set in advance, they cannot capture the full variability of real-time prices. Due to this, Hogan (2014) argues that a TOU tariff can capture only a small part of the RTP’s efficiency gain compared to a flat rate. In particular, Hogan (2014) shows that the deadweight loss due to adopting TOU rather than RTP

settings. We observe that a TOU tariff with a peak to off-peak ratio of four results in the peak load reduction of 5.7%. We also observe a 2.8% increase in off-peak load, resulting in a net increase of 1.7% in total consumption.

17 We use the optimal flat rate as a baseline tariff for this study, which is 12.5 cents/kWh under both social planner and perfectly competitive settings. We calculate the weekly expenditure of an average household under the flat rate, and determine the peak and off-peak prices corresponding to peak-to-off-peak ratios of two, three and four such that these prices result in the same weekly expenditure for the average household given that the household does not change its consumption under the TOU tariff. A similar assumption is made in the tariff design of the original field experiment such that the average participant who did not alter their electricity consumption pattern was not penalized financially under the time of use tariff (CER 2011, page 5).

18 The price ratios considered in the experiment allow us to meaningfully consider a maximum peak to off-peak price ratio of four.
is proportional to the square of the deviation of TOU rates from RTP. A simple index defined in Hogan (2014) shows how much of the variability in the real-time prices TOU rates can capture. In our context, this efficiency index for any general pricing tariff \( p_{dt} \) and the flat rate \( p \) is as follows:

\[
1 - \frac{\sum_{d,t} (w_{dt} - p_{dt})^2}{\sum_{d,t} (w_{dt} - p)^2}
\]

So for the optimal TOU rates \( p^*_m \) and the optimal flat rate \( p^* \), we write the efficiency index of the TOU rates as:

\[
1 - \frac{\sum_{m=1}^{M} \sum_{d,t \in T_m} (w_{dt} - p^*_m)^2}{\sum_{d,t} (w_{dt} - p^*)^2}
\]

Note that the efficiency index of the RTP is one and the flat-rate tariff is zero. We find that in the social planner setting, the efficiency index of annual TOU is 0.27, and the one for the seasonal TOU is 0.36. Under perfect competition, these numbers are 0.25 and 0.35, respectively. Hogan (2014) finds that the average PJM TOU index value for 2013 is 0.23 if the hourly TOU rates are updated monthly and 0.11 if TOU index is calculated at an annual basis, and concludes that even well-designed time-of-use rates might fall short of the efficiency gains generated by the real-time prices.

6.2. Consumers’ Electricity Bills and Retailers’ Profits

The policymakers are willing to promote time-based pricing schemes as long as the consumers’ electricity bills do not suffer. In our context, switching from the flat rate to TOU or RTP tariffs do not change consumers’ annual electricity bills significantly. In both the social planner and the perfectly competitive equilibrium settings, the annual electricity bills decrease for all consumers although the decrease is by less than 1% for an average consumer. The minimum reduction across all consumers is 0.02% (under annual TOU pricing) in the perfectly competitive setting and 0.03% in the social planner setting, whereas the maximum reduction is 1.5% (under RTP) in both the social planner’s and perfectly competitive settings.

Although annual electricity bills do not change significantly, monthly variations can create problems for some consumers. Figure 4 shows that all tariffs create a moderate level of variation in the average monthly electricity bills until the end of the year but the seasonal TOU pricing and RTP create the sharpest increase in the monthly bills in December. This is because the RTP can directly reflect the wholesale prices which are much higher during the month of December. In the same way, the seasonal TOU tariff can better reflect the increasing wholesale prices compared to the flat rate and annual TOU tariff as the seasonal TOU tariff has the flexibility to increase the day, night and peak prices during the Christmas season, which is the month of December.
Figure 4  Average monthly household bills: Under the social planner vs. perfect competition.

![Graph showing average monthly bills under social planner and perfect competition.]

Figure 5  The coefficient of variation in monthly electricity bills.

![Graph showing distribution of coefficient of variation across monthly bills under social planner and perfect competition.]

Figure 6  Average monthly profits for retailers: Under the social planner vs. perfect competition.

![Graph showing average monthly profits for retailers under social planner and perfect competition.]

Figure 5 shows the coefficient of variation in the monthly bills of all consumers for the social planner and perfectly competitive settings. We find that the seasonal TOU and RTP cause

The coefficient of variation for a household is defined as the standard deviation of monthly electricity bills divided by the average monthly electricity bill for that household over 2010.
relatively higher variation in the monthly electricity bills, about 0.24 for the median consumer. On the other hand, the flat rate results in the lowest variation, approximately a coefficient of variation of 0.13 for the median consumer. The annual TOU price results in a slightly higher coefficient of variation, 0.16 for the median consumer.

Retailers might be concerned about offering time-based tariffs if it creates too much volatility in their profits throughout the year. As shown in Figure 6, we find that the flat rate creates the most volatility in the retailer’s profits under both settings while the more flexible seasonal TOU tariff creates less volatility, and the RTP results in zero profits for the retailer consistently every month. In other words, the more flexible the tariff is in terms of pricing, the less volatility it creates in retailers’ profits, which provides a motivation for the retailers to offer flexible time-based tariffs. However, this can create a conflict with the consumers’ incentives as the more flexible tariffs such as the seasonal TOU tariff and RTP cause higher variation in the consumers’ monthly electricity bills.

6.3. The Change in Carbon Dioxide Emissions

One might expect that keeping the total consumption the same, time-based electricity pricing might harm the environment by increasing the carbon dioxide (CO$_2$) emissions due to electricity generation. For example, the base electricity load in the U.S. is typically covered by carbon intensive power plants such as coal-fired power plants whereas the peak load can be covered by less carbon intensive power plants such as natural gas plants or steam turbines (EIA 2017a, Table A.3; EIA 2017b, Table 6.7.A). The flattening of the demand curve may lead the base load power plants to supply more and the “greener” plants to supply less.

Next, we explore the change in CO$_2$ emissions from power plants as a result of time-based pricing. To conduct this analysis, we use the dispatch data and emissions intensity of the electricity generators in Ireland (see Appendix F for details). Figure 7(a) shows the share of electricity supply by the five largest fuel sources and other power plants in 2010. In Ireland, the CO$_2$ emissions intensity of generation is relatively constant between the peak and the off-peak hours in the region. The decrease in natural gas prices caused the multi-fuel and natural gas combined cycle plants to replace some relatively expensive coal-fired plants so coal has a lower percentage in the fuel mix, 12%. Several renewable energy sources cover 14% of the total demand in Ireland, 6% of which is

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20 This analysis on relative variation of monthly bills is similar to the one in Borenstein (2007). Note that when Borenstein (2007) calculates the “coefficient of deviation”, he uses the customer’s average bill for that month of the year as Borenstein (2007) has multiple years of data on monthly bills. Given that we have about one year of historical data, we use the average bill over a year when we calculate the coefficient of variation. Table 2 in Borenstein (2007) shows a median coefficient of deviation of about 0.09 for the flat rate and annual TOU rates, and about 0.37 for RTP.

21 Note that under both the social planner and perfectly competitive settings, the total annual profit of a retailer is zero.
Figure 7  (a) The share of supply from the major fuel types. (b) The supply for each fuel type as a function of system load.

![Figure 7](image)

<table>
<thead>
<tr>
<th>Table 8 Comparison of carbon emissions.</th>
<th>Social Planner</th>
<th>Perfect Competition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in Emissions</td>
<td>Annual TOU</td>
<td>Seasonal TOU</td>
</tr>
<tr>
<td></td>
<td>-0.006%</td>
<td>-0.001%</td>
</tr>
</tbody>
</table>

The change in total yearly emissions, compared to the flat rate, under different market environments.

wind energy. The base load also includes peat production, which makes up 6% of the total load\textsuperscript{22}. Figure 7(b) summarizes how the power plants with the aforementioned fuel sources and the peaker oil-fired power plants are dispatched as the system load increases. The use of coal-fired plants increase towards mid-ranges of load. During peak hours, coal, natural gas and renewable power plants are dispatched together with dirtier peaker plants using oil or distillate fuel. Due to this structure, the emission intensity of generation during peak and off-peak hours is basically the same, with the base-load being slightly dirtier.

Table 8 shows that given the small difference in the CO\textsubscript{2} emissions intensity of the peak and base load power plants in Ireland, time-based pricing schemes do not have a significant impact on total CO\textsubscript{2} emissions, compared to those under the flat rate. We find that emissions decrease during peak periods, which is offset by the increase in emissions during off-peak periods. However, the effects of time-based pricing on CO\textsubscript{2} emissions can be more significant and directionally different in an electricity market with a different energy mix.

To test this hypothesis, we calculate the impact of time-based pricing on the CO\textsubscript{2} emissions in ten U.S. regions defined by the EPA, using the Emissions Quantification Tool (EQT), which contains

\textsuperscript{22}In comparison, in the U.S., 31% of generation comes from coal, 34% is natural gas, 20% is nuclear, 15% are renewables, and the rest is petroleum (EIA 2017).
the generation portfolio of each of these ten U.S. regions. We input the estimated system load of Irish consumers under flat-rate and each time-based pricing scheme. These inputs are the ones we estimated using the Irish data, as we don’t have data on the electricity consumption profiles in each U.S. region under flat rate and time-based pricing. Further details of our analysis are provided in Appendix G.

We find that under the social planner setting, moving from flat rate to time-based pricing decreases CO₂ emissions in the California and Northwest regions, which have a lower share of fossil-fuel powered generation, and a higher share of hydro or renewable plants. The emissions increase by less than 0.1% in the other 8 regions.

Under perfect competition, emissions increase by less than 1% in all regions. The detailed results for each region can be found in Appendix G. The percentage change in emissions is small for all U.S. regions but the absolute change in emissions is more significant for larger markets. To put this in context, the increase in the Great Lakes region switching from flat rate to annual TOU is 353K metric tons of CO₂. This amount is equal to emissions from 75K passenger vehicles driven for one year, or 38K homes electricity use for one year or 40 million gallons of gasoline consumed. The decrease in the Northwest region is about 55K metric tons which equals to emissions from 12K passenger vehicles driven for one year, or 6K homes electricity use for one year or 6.2 million gallons of gasoline consumed. The finding that CO₂ emissions do not increase much can make it easier to adopt time-based tariffs from an environmental perspective. However, further research is needed to explore this for the US markets.

7. Discussion
Electricity retailers have been rapidly introducing time-based pricing programs following the global wide-spread adoption of advanced metering infrastructure (AMI). Time-based pricing strategies such as the TOU tariff or RTP can encourage customers to shift their peak consumption to off-peak times, i.e., flatten their demand curve. In the short term, the flattened demand curve improves the utilization of the power plants, increases reliability, reduces grid congestion charges and the cycling costs for the power plants.

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23 EQT is developed by the Pacific Northwest National Laboratory, tasked by the U.S. Department of Energy, and it calculates the impact of smart grid projects on the CO₂, sulfur dioxide (SO₂) and nitrogen oxide (NOₓ) emissions. https://gridpiq.pnnl.gov

24 Holland and Mansur (2008) quantify the changes in within-day load variation on emissions, by estimating daily total emissions as a function of the coefficient of variation and the mean of the daily load for 10 U.S. electricity markets. They also conduct a simulation study with hourly aggregate system load data, to measure the change in emissions due to changes in system load across different days, and their findings are directionally similar to ours for the change in emissions in these regions (Holland and Mansur 2008, Table 6).

25 The emission equivalences are calculated based on U.S. Environmental Protection Agency (2017).
While electricity retailers seek to flatten the demand curve via time-based tariffs, the consumers and policymakers, on the other hand, wish to reduce energy bills and environmental emissions. In this study, we empirically investigate the short-term effects of time-based tariffs on peak consumption, consumers’ electricity bills, retailers’ profit and CO$_2$ emissions. To answer these questions, we build a structural estimation model and analyze a data set from an Irish field experiment, consisting of the half-hourly electricity consumption of over three thousand households, combined with the wholesale price, system load and generation data. The households that participated in this field experiment did not have any smart appliances so they responded to price changes by manually changing the time and nature of their electricity use. In the future, smart appliances might track and respond to the changes in the electricity prices. This would alleviate the burden of monitoring the prices off the consumers, which is especially challenging with the hourly changing prices of RTP schemes.

Our counterfactual study considers the flat rate, TOU and RTP tariffs for the perfect competition and the social planner settings. Interestingly, given a fixed time horizon for evaluation, it is possible to design a flexible TOU tariff, e.g. seasonal TOU tariff, with pre-determined rates that is simple and predictable, which can lower the peak load as much as RTP. However, RTP, being able to change the price in each hour, performs better in terms of reducing the hourly peaks.

We find that the annual electricity bills decrease only slightly when consumers switch from the flat rate to time-based tariffs, but they may face significant volatility in bills from month to month under time-based tariffs. Therefore, the minor reduction in bills might not justify the cost of switching to a new tariff and having higher volatility in their monthly electricity bills for the consumers. Consequently, many consumers might not opt in to a time-based tariff, and more consumers might stick with a time-based tariff if it is introduced as the default tariff. According to the U.S. Department of Energy (2016) report on consumer behavior studies on time-based rate programs, opt-out enrollment rates are 92% compared to only 15% under voluntary enrollment. In fact, markets such as Ireland, Italy, and Ontario (Canada) have already introduced such opt-out policies for the electricity consumers (Faruqui et al. 2014, CER 2014). Our findings provide further support in this direction.

Moreover, we observe that the flat rate creates the most volatility in the retailer’s profit from month to month, and the more flexible a tariff in terms of pricing, the less volatility it creates in retailer’s profits throughout the year. Hence, opt-out policies also align with the retailer’s incentives. Moreover, retailers incur additional costs in the design and implementation of time-based rates for market research, recruitment campaigns, customer technology devices, etc. U.S. Department of Energy (2016) finds that the magnitude of the recruitment efforts differs substantially between
opt-in and opt-out approaches, and opt-out recruitment provides more cost-benefit advantages as it takes less effort to default customers on these rates than to enroll and educate volunteers.

Finally, we find that switching from the flat rate to time-based tariffs would not change CO$_2$ emissions from electricity generation in Ireland significantly. However, the magnitude and the direction of change in CO$_2$ emissions depends on the energy mix of the dispatched generation and the electricity market structure, and further research is needed to explore this for the US markets.

References


Appendix A: The Recruiting Process for the Customer Behavior Trials

CER recruited participants, and installed smart meters to the participant homes through 2008 and early 2009 under a voluntary opt-in program, which received a response rate of 30%. Electric Ireland was the only retailer serving the residential electricity market during the recruiting phase of the customer behavior trials. Thus, the randomly chosen initial pool of candidates is representative of the entire population of residential customers. Invitations to participate in the trial were sent out in five phases. Each wave of respondents who opted in were profiled to check if the sample thus far was representative of the national profile (on the basis of consumption profiling), and the deviations were corrected by structuring the invitations in the following phase accordingly. However, due to the voluntary opt-in methodology, there is a slight under-representation among lowest and highest usage customers, albeit the deviations are relatively low (CER 2011, Appendix 3). The two groups (people who responded and did not respond) were found to be similar across social grade, employment status, house type, age and use of electricity by appliance (CER 2011, pg. 51).

Appendix B: Comparison of Consumption for Households With and Without Survey Data

We have half-hourly consumption data for 4225 households initially, some of which are excluded from the analysis. First, we sum the half-hourly observations and use hourly consumption values. Next, the households who did not participate in the survey are excluded from our analysis. To see if this affects the representativeness of the sample, we bootstrap the difference between the median daily consumptions in households with and without survey information (see Efron and Tibshirani (1986) for the description of the methodology we use here). We find that there is no significant difference in consumption between the surveyed households and the whole sample considering a 95% confidence interval.

Next, we focus on the subset of households that participated in the survey, and make pairwise comparisons of TOU tariff groups, A, B, C, D, the control group E, and the weekend group W. Table 9 shows the bootstrapped difference in median daily household consumption, and the standard errors of this statistic. For each pairwise comparison, the 95% confidence interval for the differences in medians includes 0, and hence, we conclude that there is no significant difference between the consumption profiles of these tariff groups. The weekend group also does not show any significant difference from the other tariff groups in terms of its consumption profile, and we exclude this group from the dataset as it includes only 86 households, and its pricing structure does not follow the other tariff groups.

After the steps listed above, a total of 3396 households remain in the dataset. We exclude 6 households whose consumption values are outliers compared to the rest of the dataset. 3 of these households have very small consumption, and their average peak period consumption is less than 0.1 kWh. The other 3 households have significantly higher consumption than the rest of the households, with an average night period consumption of more than 2 kWh.

Finally, we treat some missing observations and extra consumption readings. The extra readings occur on Sunday, October 31st 2010 at 02:00, which was the end of Daylight Savings Time. The consumption of households was recorded twice for that hour, and we use the average of the two values. Likewise, there is an hour of missing readings on Sunday, March 28th, which is the beginning of Daylight Savings Time. We
Table 9  Bootstrapped differences in median daily consumption.

<table>
<thead>
<tr>
<th>Groups</th>
<th>Difference in Medians</th>
<th>Groups</th>
<th>Difference in Medians</th>
<th>Groups</th>
<th>Difference in Medians</th>
<th>Groups</th>
<th>Difference in Medians</th>
<th>Groups</th>
<th>Difference in Medians</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-W</td>
<td>-0.11 (1.87)</td>
<td>B-W</td>
<td>0.24 (2.05)</td>
<td>C-W</td>
<td>-0.16 (1.76)</td>
<td>D-W</td>
<td>-0.35 (1.93)</td>
<td>E-W</td>
<td>-1.12 (1.79)</td>
</tr>
<tr>
<td>A-E</td>
<td>1.01 (0.56)</td>
<td>B-E</td>
<td>1.35 (0.87)</td>
<td>C-E</td>
<td>0.96 (0.60)</td>
<td>D-E</td>
<td>0.77 (0.61)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A-D</td>
<td>0.23 (0.65)</td>
<td>B-D</td>
<td>0.58 (0.83)</td>
<td>C-D</td>
<td>0.19 (0.58)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A-C</td>
<td>0.05 (0.59)</td>
<td>B-C</td>
<td>0.40 (0.94)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A-B</td>
<td>-0.35 (0.83)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Standard errors are given in parentheses.

extrapolate the consumption on the missing hour by adding the previous half-hours consumption reading to
the immediately following half-hours consumption reading.

Appendix C: Computation of Wholesale Prices

The wholesale price is the sum of the following charges (CER 2010c, 2013):

- **Wholesale Generation Costs:** This is the price paid by the suppliers when buying electricity from the
  wholesale market, and it is the sum of the following charges:

  1. System Marginal Price (SMP): This is the market clearing price for generators. The half-hourly
     realized values of the SMP for the year 2010 in Ireland are available (SEMO 2014a).

  2. Capacity Charges: The capacity payments mechanism allocates a monthly aggregate capacity
     charge to obtain the capacity price per MWh. For example, total capacity payments in January
     2010 were €55.4M (SEMO 2010). We divide this by the aggregate system load in the month of
     January, and find a unit capacity price of €8.1 per MWh.

  3. Market Operator Charges: This is recovered from suppliers on a MWh basis to cover the operating
     costs and regulated revenue of the market operator, and is taken as €0.68 per MWh for the year
     2010 (SEMO 2014b).

  4. Imperfections Charges: These are imbalance costs and testing charges, borne by the market oper-
     ator, and the 2010 charge is set as €3.14 per MWh (SEMO 2014b).

- **Network Charges:** These are transmission and distribution charges and are paid by suppliers on a
  cents/kWh basis; summing up to an average of 4 cents/kWh (CER 2009a).

- **Supply Costs:** These cover the operating costs of the supplier and are regulated each year based on the
  projected expenses and revenues. In 2010, the annual allowed revenues were €120M, €23M of which
  is set as the supply margin, and €8M is set as the depreciation costs (CER 2009d, Appendix B). We
  inflate the wholesale generation costs by the same ratio, by approximately 30%.

- **Public Service Obligation Levy:** The PSO levy is charged to all electricity consumers for the additional
  costs incurred by the suppliers in meeting their obligations to purchase electricity from sustainable,
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renewable, and indigenous sources. This is set as zero for the period 1st of October 2009 to the 30th of September 2010. After September 2010, it is set around €2 per month for each consumer, so we assume it is negligible for the last 3 months of 2010 as well (CER 2009b).

Appendix D: The Utility Maximization Problem and Demand Model with a Quadratic Utility Function

We described in Section 3 that each household $n$ chooses its electricity consumption, $x^n$, to maximize its utility $u^n(x^n)$, where the electricity consumption vector, $x^n = (x^n_{dt})$, is defined over the households $n \in \{1, \ldots, N\}$ and the planning horizon, that is, over the weekdays $d \in \{1, \ldots, D\}$ and the hours of the day $t \in \{1, \ldots, T\}$. As stated in Section 5, we assume that this utility function $u^n(x^n)$ for household $n$ is quadratic as follows:

$$u^n(x^n) = \frac{1}{2}(x^n)^T B_n^{-1}(x^n - 2\alpha^n)$$

where $\alpha^n$ is a vector denoting the parameters $\alpha^n_{dt}$ in the demand equation (3). The matrix $B_n$ is symmetric and negative definite. We let $dt$ denote the index corresponding to day $d$ and hour $t$ and let $\beta^n_{dt,ds}$ denote the entries of matrix $B_n$ where

$$\beta^n_{dt,ds} = \begin{cases} 
\beta^n_{dt} - 2\theta_1 - 2\theta_2 & \text{if } s = t \text{ and } t \in \{3, \ldots, T-2\}, \\
\beta^n_{dt} - 2\theta_1 - \theta_2 & \text{if } s = t \text{ and } t \in \{2, T-1\}, \\
\beta^n_{dt} - \theta_1 - \theta_2 & \text{if } s = t \text{ and } t \in \{1, T\}, \\
\theta_1 & \text{if } |t-s| = 1, \\
\theta_2 & \text{if } |t-s| = 2, \\
0 & \text{elsewhere.} 
\end{cases}$$

Note that substitution between hours is limited to hours with the same day.

We assume that the budget constraint is binding in the utility maximization problem of household $n$ in (1). Therefore, (1) simplifies to the unconstrained maximization problem

$$\max_{x^n} u^n(x^n) - \sum_d \sum_t p_{dt} x^n_{dt} + Y^n.$$ 

The solution to this problem given by the first order condition

$$p = B_n^{-1}(x^n - \alpha^n),$$

is unique because $B_n$ is invertible (since it is negative definite). This yields the linear demand equations

$$x^n = \alpha^n + B_n p.$$ 

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26 There are $N = 3390$ households in the field experiment and $D = 256$ weekdays during the field experiment and $T = 24$.

27 We assume that the household’s budget does not limit its electricity expenditure because the electricity bill is small relative to the household budget, that is, $x^n_0 > 0$. 

Appendix E: Choice of the Substitution Model

As introduced in Section 4, there is limited variation in prices charged in our customer trial data. Hence, we only have the flexibility to estimate up to 3 independent substitution parameters. We experimented with alternative parsimonious structures, which have up to 3 substitution parameters, and found stronger evidence of local substitution within neighboring hours rather than a global substitution pattern that considers the prices several hours ahead of the current period. (For example, in one model, we included for each hour a single parameter to represent local substitution within 4 hours, together with another parameter that looks at the substitution to 12 hours ahead. We found the local parameter to be statistically significant, whereas there was no significant global effect.) Thus we compare models that consider 0, 1, 2 or 3 hours of substitution locally around each hour. Specifically, the consumption in any given hour increases (decreases) by $\theta_i$ units for each unit of higher (lower) price in the $i = \{0, 1, 2, 3\}$ hours before and after.

The prediction power of these models are similar in terms of the residual mean squares (MS). In each of the models, some substitution parameters are significant, so we decide to include the substitution effects. Specifically, we find that in the model with one-period of substitution, $\theta_1$ is significant; in the model with two-period substitution, both $\theta_1$ and $\theta_2$ are significant; and in the model with three-period substitution, $\theta_2$ loses significance, and only $\theta_1$ are $\theta_3$ are significant. Given that at most two of the parameters are significant, we proceed with the two-period substitution model.

As a final metric of comparison, we also investigate which model captures the peak load reduction in the experiment the best. For this, we look at the predicted peak load reduction for each tariff group under each of these models when we charge the actual experiment prices to households. We compare these predictions with the peak load reduction observed for each tariff group against the control group, during the actual experiment. The results of this analysis is shown in Table 10, and models perform very similarly.

<table>
<thead>
<tr>
<th>Models</th>
<th>Experiment</th>
<th>No Substitution</th>
<th>1 Period</th>
<th>2 Period</th>
<th>3 Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>-2.51%</td>
<td>-0.66%</td>
<td>-0.65%</td>
<td>-0.63%</td>
<td>-0.61%</td>
</tr>
<tr>
<td>B</td>
<td>-1.65%</td>
<td>-1.83%</td>
<td>-1.81%</td>
<td>-1.80%</td>
<td>-1.79%</td>
</tr>
<tr>
<td>C</td>
<td>-5.48%</td>
<td>-4.61%</td>
<td>-4.60%</td>
<td>-4.59%</td>
<td>-4.58%</td>
</tr>
<tr>
<td>D</td>
<td>-6.09%</td>
<td>-5.82%</td>
<td>-5.82%</td>
<td>-5.82%</td>
<td>-5.82%</td>
</tr>
</tbody>
</table>

The percentages are the change in annual peak load for each tariff group compared to the control group.

Appendix F: Computation of Carbon Emissions in Ireland

In Section 6, we have predicted the household demand for the optimal flat-rate and time-based pricing tariffs. In this section, we use those predictions together with the dispatch data of the electricity generators in Ireland, to compare the expected emissions under each of these tariffs.

Since the generators are dispatched to supply the entire system load, we first calculate the total system load when residential consumers are under flat-rate pricing versus under time-based pricing. The system load
is the sum of the residential and the non-residential (commercial and industrial) loads. We assume that the non-residential load remains the same, and we approximate it as follows: We calculate the total consumption of households participating in the experiment under a flat rate of 14.1 cents/kWh (the rate charged to residential customers in Ireland in 2010), over all observations in 2010. At the time of the experiment, all households were served by a single retailer. So the aggregate residential consumption in Ireland is assumed to mimic the consumption of the households in the experiment, except for a scaling factor. (The residential share of the total annual load is 33.62% (Howley et al. 2014).) Afterwards, the non-residential part of the system load is taken as the difference between the actual system load in 2010 and the calibrated residential load, for each hour in 2010. Finally, the residential load component of the total system load is assumed to be equal to what we predicted from the empirical model in Section 6.

Next, we calculate the empirical distribution of emissions for each level of system load, using the actual observed hourly dispatch decisions in 2010. For each hour, we look at the portfolio of generators dispatched to supply the total load for that hour using data from Single Electricity Market Operator (SEMO) (2014a). We aggregate this data by fuel type to calculate the fuel mix corresponding to each observation of the system load. Then, we calculate the CO$_2$ emissions in each hour using the fuel emission factors (SEAI 2014) and the heat conversion factors for typical power plants (EURELECTRIC Upstream Sub-Group and VGB 2003). For example, the load that comes from coal-fired power plants is multiplied by the emissions factor for coal, which is 0.341 tonnes CO$_2$/MWh, and then scaled by the heat conversion factor for coal, which is 0.35. The total emissions in that hour is the sum of the emissions from each fuel source, with renewables having no contribution. Then, we discretize the system load into 50 MWh intervals, to obtain the expected emissions for each of these load intervals.

Finally, using the predicted system load together with the empirical distribution of emissions, we compute the expected emissions for the optimal flat-rate and time-based pricing tariffs.

**Appendix G: Computation of Carbon Emissions in the U.S.**

For calculating the US emissions, we use the Emissions Quantification Tool (EQT), which calculates the change in emissions for 10 predefined US regions$^{28}$. EQT calculates expected emissions using the Avoided Emissions and Generation Tool (AVERT) developed by the U.S. Environment Protection Agency (EPA 2015). AVERT analyzes the hourly historical dispatch and emissions data for fossil-fuel power plants and maps generation quantity to emissions through a Monte Carlo analysis for each of the given US regions. EQT compares the total expected emissions under two load profiles: The input and output load profiles representing the load profiles in a region before and after the application of a smart grid project, respectively. Computation of the Input and Output Load Profiles: We do not have information on the residential load profile for the U.S. regions. Hence, the system load in the U.S. regions before and after time-based pricing is assumed to be the same as the Irish system load except for a scaling factor. The scaling factor is selected separately for each of the 10 regions, such that the peak load for the Irish load is equal to the peak load in each region, resp.

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$^{28}$ The Environment Protection Agency (EPA) splits the country into the following 10 regions: Northwest, Rocky Mountains, California, Southwest, Upper Midwest, Lower Midwest, Texas, Northeast, Great Lakes, Southeast.
As the input load profiles, we use the counterfactual system load under the optimal flat rate for each market setting. In a similar manner, the counterfactual system load profiles under the optimal time-based pricing schemes are used as the output load profiles. In order to go from the counterfactual residential demand profile to the counterfactual system load profile, we assume that the non-residential (commercial and industrial) load remains the same while the residential load under each tariff is calculated from the empirical model.

We approximate the non-residential load for 2010 as follows: We calculate the total consumption of households participating in the experiment under a flat rate of 14.1 cents/kWh (the rate charged to residential customers in Ireland in 2010), over all observations in 2010, which is 29.7 million MWh. The aggregate residential consumption in Ireland is assumed to mimic the consumption of the households in the experiment, except for a scaling factor. The residential share of the total annual load is 33.62% (Howley et al. 2014). Thus, the experiment load profile is scaled such that the total residential load equals 33.62% of the total annual system load over 2010, which is 11.2 TWh. Afterwards, the non-residential part of the system load is taken as the difference between the actual system load in 2010 and the calibrated residential load, for each hour in 2010.

Finally, we only compute the change in emissions due to changed pricing in weekdays, hence we assume there is no change to the system load during holiday periods. The baseline emissions under each region under the flat rate, and the change in emissions under TOU rates are presented in Table 11.

<table>
<thead>
<tr>
<th>EPA Region</th>
<th>Base CO(_2) Emissions</th>
<th>Change in CO(_2) Emissions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Social Planner</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A-TOU</td>
</tr>
<tr>
<td>Texas</td>
<td>143.7m</td>
<td>38.3k</td>
</tr>
<tr>
<td>Northeast</td>
<td>38.5m</td>
<td>9.5k</td>
</tr>
<tr>
<td>Upper Midwest</td>
<td>133.5m</td>
<td>111.7k</td>
</tr>
<tr>
<td>Great Lakes</td>
<td>305.1m</td>
<td>165.2k</td>
</tr>
<tr>
<td>Lower Midwest</td>
<td>98.7m</td>
<td>47.3k</td>
</tr>
<tr>
<td>Southeast</td>
<td>358.9m</td>
<td>87.9k</td>
</tr>
<tr>
<td>Northwest</td>
<td>32.7m</td>
<td>-59.4k</td>
</tr>
<tr>
<td>California</td>
<td>32.2m</td>
<td>-2.9k</td>
</tr>
<tr>
<td>Southwest</td>
<td>55.9m</td>
<td>45.3k</td>
</tr>
<tr>
<td>Rocky Mountains</td>
<td>35.2m</td>
<td>15.5k</td>
</tr>
</tbody>
</table>

All numbers are given in metric tons of CO\(_2\).
Online Companion to “An Analysis of Time-Based Pricing in Retail Electricity Markets”

Appendix EC.1: The Pricing Problem

In this section, we characterize the solution to the social planner’s pricing problem described in Section 3. We assume that the consumers have a quadratic utility function for electricity consumption following (5) in Appendix D. We consider all three types of pricing regimes introduced in Section 6: the flat rate, the TOU tariff and the RTP. Under the flat rate, \( p_{dt} = p, \forall d, t \). Under the TOU tariff, the planning horizon is divided into \( M \) periods, where \( T_m \) is the set of days and hours in period \( m \) for \( m = 1, \ldots, M \). The retailer chooses the price, \( p_m \), for period \( m \), i.e., \( p_{dt} = p_m \) for all \( dt \in T_m \). Finally under RTP, the retailer can choose a separate price \( p_{dt} \), for each day \( d \in \{1, \ldots, D\} \) and hour \( t \in \{1, \ldots, T\} \). For all of these tariffs, a fixed fee of \( A \) is charged in addition to the variable rates.

EC.1.1. Social Planner’s Setting

Next, we show that there is a unique solution to the social planner’s pricing problem given in (2) under the flat rate, TOU and RTP tariffs.

**Proposition EC.1.** The optimal two-part tariffs under the social welfare maximization for each of the three pricing schemes are:

(a) The optimal flat rate:
\[
p^* = \frac{\sum_{n,d,t} w_{dt} \beta^n_{dt}}{\sum_{n,d,t} \beta^n_{dt}}.
\]

(b) The optimal TOU tariff: For all \( m = 1, \ldots, M \), \( p^*_m \) jointly solve the following \( M \) equations
\[
\sum_{n,d,t} w_{dt} \left( \sum_{s \in T_m^d} \beta^n_{dt,ds} \right) = \sum_{k=1}^M p_k \left( \sum_{n,dt \in T_m} \sum_{s \in T_d^k} \beta^n_{dt,ds} \right),
\]
where \( T_m^d = \{ t : dt \in T_m \} \).

(c) The optimal RTP: \( p^*_{dt} = w_{dt} \).

In all pricing schemes, the optimal fixed fee \( A^* \) can be found by plugging in the optimal prices into the budget constraint.

**Proof.** As explained in Section 3, the budget constraint of the social planner’s problem, i.e., equation (2), is binding at the optimal solution. That is,
\[
AN = \sum_{n,d,t} w_{dt} x^n_{dt} - \sum_{n,d,t} p_{dt} x^n_{dt}.
\] (EC.1)

Substituting (5) and (EC.1) into the social planner’s objective function leads to the following unconstrained optimization problem:
\[
\max_p \sum_n \left( \frac{1}{2} (x^n)^T B_n^{-1} (x^n - 2\alpha^n) - w x^n \right). \tag{EC.2}
\]

We know from Equation (7) that \( x^n = \alpha^n + B_n p \). Substituting this into (EC.2), we arrive at the following problem:
\[
\max_p \sum_n \left( \frac{1}{2} (\alpha^n + B_n p)^T B_n^{-1} (-\alpha^n + B_n p) - w (\alpha^n + B_n p) \right)
= \max_p \sum_n \left( -\frac{1}{2} \alpha^n B_n^{-1} \alpha^n + \frac{1}{2} p^T B_n p - w \alpha^n - w B_n p \right).
\]
After dropping the terms that do not involve the decision variables $p$, the social planner’s problem can equivalently be written as:

$$\max_p \frac{1}{2} \sum_{n,d,t} p_{dt} \left( \sum_s \beta_{dt,ds}^n P_{ds} \right) - \sum_{n,d,t} w_{dt} \left( \sum_s \beta_{dt,ds}^n P_{ds} \right).$$  \hfill (EC.3)

First, consider the flat-rate pricing, i.e., $p_{dt} = p$ for all $d, t$. Then, the problem in (EC.3) becomes choosing a single price $p$ so as to

$$\max_p \frac{1}{2} p^2 \left( \sum_{n,d,t,s} \beta_{dt,ds}^n \right) - p \sum_{n,d,t,s} \beta_{dt,ds}^n w_{dt}.$$  

The first-order condition gives:

$$p = \frac{\sum_{n,d,t,s} w_{dt} \beta_{dt,ds}^n}{\sum_{n,d,t,s} \beta_{dt,ds}^n},$$

which is sufficient for optimality as long as $\sum_{n,d,t,s} \beta_{dt,ds}^n < 0$. By definition of $B_n$, we have $\sum_s \beta_{dt,ds}^n = \beta_{dt}^n$ for each $t$. Then,

$$p^* = \frac{\sum_{n,d,t} w_{dt} \beta_{dt}^n}{\sum_{n,d,t} \beta_{dt}^n},$$  \hfill (EC.4)

which completes the proof of case (a). Note that substituting (EC.4) into (EC.1) determines the optimal fixed fee for the flat rate, $A_p^*$. 

Second, we consider the TOU tariff. In this case, $p_{dt} = p_m$ for $dt \in T_m$ for $m = 1, \ldots, M$. Thus, the social planner’s problem in (EC.3) becomes:

$$\max_{p_m} \sum_{m=1}^M \left\{ \frac{1}{2} p_m \sum_{n,d,t} \left( \sum_{k=1}^M \sum_{s \in T^d_k} \beta_{dt,ds}^n P_{ds} \right) - \sum_{n,d,t} w_{dt} \left( \sum_{k=1}^M \sum_{s \in T^d_k} \beta_{dt,ds}^n P_{ds} \right) \right\}. $$

Then, for each $m = 1, \ldots, M$, the first order condition with respect to $p_m$ is

$$0 = p_m \sum_{n,d,t} \sum_{s \in T^d_m} \beta_{dt,ds}^n + \frac{1}{2} \sum_{k=1, k \neq m}^M p_k \left( \sum_{n,d,t} \sum_{s \in T^d_k} \beta_{dt,ds}^n + \beta_{dt,ds}^n \right) - \sum_{n,d,t} w_{dt} \left( \sum_{s \in T^d_m} \beta_{dt,ds}^n \right).$$

Since $B_n$ is symmetric by definition, we have $\beta_{dt,ds}^n = \beta_{ds,dt}^n$, the first-order condition with respect to $p_m$ can be written as:

$$0 = \sum_{k=1}^M p_k \left( \sum_{n,d,t} \beta_{dt,ds}^n \right) - \sum_{n,d,t} w_{dt} \left( \sum_{s \in T^d_m} \beta_{dt,ds}^n \right) \quad \text{for all } m.$$

These constitute $M$ equations with $M$ unknowns. If these equations are linearly independent, then they give rise to a characterization of the unique optimal price for every period. This completes the proof of case (b). Substituting the optimal prices into (EC.1) determines the optimal fixed fee for the TOU tariff, $A_p^*$. 

In case of RTP, let $S_t = \{ s : \beta_{dt,ds}^n \neq 0 \}$ (i.e., there is substitution between hours $t$ and $s$) for each hour $t$. Then, the first-order condition for the social planner’s problem in (EC.3) for each day $d$ and hour $t$ becomes:

$$0 = \sum_n \beta_{dt,dt}^n P_{dt} + \frac{1}{2} \sum_{n,s \in S_t, s \neq t} (\beta_{dt,ds}^n + \beta_{dt,ds}^n) P_{ds} - \sum_{n,s \in S_t} w_{ds} \beta_{ds,dt}^n.$$
Since $B_n$ is symmetric by definition, we have $\beta_{dt,ds}^n = \beta_{ds,dt}^n$. The first-order conditions become:

$$0 = \sum_{n,s \in S_t} \beta_{ds,dt}^n p_{ds} - \sum_{n,s \in S_t} \beta_{ds,dt}^n w_{ds}.$$

The unique solution to these set of equations is $p_{dt}^* = w_{dt}$. Substituting these into (EC.1) gives $A_R^* = 0$. □

**EC.1.2. The Equilibrium in a Perfectly Competitive Market**

Under perfect competition, retailers want to recover their marginal cost of production, and do not charge a markup on it. Under the retail electricity market setting, the marginal cost of getting one unit of supply to sell is given by the wholesale prices $w = (w_{dt})$ in every hour $t$ of every day $d$. Suppose the price tariff in the perfectly competitive equilibrium is given by $(p^+, A^+)$, then the retailers’ total marginal cost is equal to $\sum_n w \cdot x^n(p^+)$. Under the perfect competition setting, the retailers directly price at the marginal cost, i.e., $p^+ = w$ and set $A^+ = 0$. As a consequence, $\sum_n w \cdot x^n(p^+) = \sum_n p^+ \cdot x^n(p^+)$. In order to compare the social planner’s setting to the perfect competition setting, we assume that the retailers recover part of their marginal cost through a fixed fee which is equal to that of the social planner. In this way, the perfectly competitive tariffs still have the two-part tariff structure used in Ireland. Interested readers can see Appendix EC.5 for the description of a perfectly competitive equilibrium without the fixed fee.

**Proposition EC.2.** Let $A_F^*$, $A_T^*$ be the social planner’s optimal fixed fee under flat rate and TOU tariffs, respectively. Under a perfectly competitive equilibrium

(a) If an optimal flat rate, $p^+$, exists, it solves a quadratic equation and is given by:

$$p^+ = \frac{\sqrt{\sum n,d,t \left( \alpha_{dt}^n - \sum_s w_{dt} \beta_{dt,ds}^n \right)^2 + 4 \left( \sum n,d,t,s \beta_{dt,ds}^n \left( \sum n,d,t,s w_{dt} \alpha_{dt}^n - A_F^* N \right) - \sum n,d,t (\alpha_{dt}^n - \sum_s \beta_{dt,ds}^n) \right)}}{2 \left( \sum n,d,t,s \beta_{dt,ds}^n \right)}.$$

(b) The optimal TOU prices, $p_{m}^*$, satisfy

$$\sum_{n,d,t \in T_m} \left( p_m^* \left( \sum_{k=1}^{M} \sum_{s \in T_k^d} \beta_{dt,ds}^n P_k^* \right) + p_m^* \alpha_{dt}^n - \left( \sum_{k=1}^{M} \sum_{s \in T_k^d} w_{dt} \beta_{dt,ds}^n P_k^* \right) - w_{dt} \alpha_{dt}^n + \frac{A_T^*}{D_T} \right) = 0,$$

for all $m$, where $T_k^d = \{ t : dt \in T_k \}$.

(c) The optimal real-time prices are $p_{dt}^* = w_{dt}$, for all $d,t$.

**Proof.** First, consider the flat-rate pricing, i.e., $p_{dt} = p$ for all $d,t$. Under this pricing scheme, the retailers’ total marginal cost for supply is given by $\sum_{n,d,t} w_{dt} x^n_{dt}(p)$. By assumption, retailers recover part of their costs by using a fixed fee that is equal to that of the social planner. This fixed fee equals to $A_F^*$ per household under the flat rate. Then, the total revenues collected from the households is equal to $A_F^* N + \sum_{n,d,t} p x^n_{dt}(p)$. Since perfectly competitive retailers do not charge a markup over their cost, the flat rate in a perfectly competitive equilibrium is

$$p^+ = \frac{\sum_{n,d,t} w_{dt} x^n_{dt}(p^+) - A_F^* N}{\sum_{n,d,t} x^n_{dt}(p^+)}.$$

Then, the household demand equation given in (3) can be equivalently written as

$$x^n_{dt}(p^+) = \alpha_{dt}^n + \sum_s \beta_{dt,ds}^n p_{ds}^+,$$

for all $d,t$. (EC.7)

---

29 Incidentally, Joskow and Tirole (2006) considers this exact pricing scheme for perfect competition (see page 804).
Substituting this in (EC.6) and rearranging the terms, we find that \( p^+ \) solves the following quadratic equation:

\[
0 = p^+ \sum_{n,d,t} x_{dt}^n(p^+) - \sum_{n,d,t} w_{dt} x_{dt}^n(p^+) + A^*_F N
\]

\[
= p^+ \sum_{n,d,t} \left( \alpha_{dt}^n + \sum_s \beta_{dt,ds}^n p^+ \right) - \sum_{n,d,t} w_{dt} \left( \alpha_{dt}^n + \sum_s \beta_{dt,ds}^n p^+ \right) + A^*_F N
\]

\[
= (p^+)^2 \sum_{n,d,t,s} \beta_{dt,ds}^n + p^+ \sum_{n,d,t} \left( \alpha_{dt}^n - \sum_s w_{dt} \beta_{dt,ds}^n \right) - \sum_{n,d,t} w_{dt} \alpha_{dt}^n + A^*_F N = 0.
\]

This quadratic equation has the following roots:

\[
p_1^+ = -\frac{\sqrt{\left[ \sum_{n,d,t} \left( \alpha_{dt}^n - \sum_s w_{dt} \beta_{dt,ds}^n \right) \right]^2 + 4 \left( \sum_{n,d,t,s} \beta_{dt,ds}^n \right) \left( \sum_{n,d,t} w_{dt} \alpha_{dt}^n - A^*_F N \right) - \sum_{n,d,t} \left( \alpha_{dt}^n - \sum_s \beta_{dt,ds}^n \right)}}{2 \left( \sum_{n,d,t,s} \beta_{dt,ds}^n \right)},
\]

\[
p_2^+ = \frac{\sqrt{\left[ \sum_{n,d,t} \left( \alpha_{dt}^n - \sum_s w_{dt} \beta_{dt,ds}^n \right) \right]^2 + 4 \left( \sum_{n,d,t,s} \beta_{dt,ds}^n \right) \left( \sum_{n,d,t} w_{dt} \alpha_{dt}^n - A^*_F N \right) - \sum_{n,d,t} \left( \alpha_{dt}^n - \sum_s \beta_{dt,ds}^n \right)}}{2 \left( \sum_{n,d,t,s} \beta_{dt,ds}^n \right)}.
\]

From the consumer’s utility maximization problem given in (1), the net surplus of household \( n \) under prices \( p \) is given by

\[
f^n(p) = u^n(x^n(p)) - p \cdot x^n(p).
\]

Next, we characterize the difference between the consumer surplus for prices \( p_1^+ \) and \( p_2^+ \). Substituting the household’s utility function given in equation (5), we get

\[
f^n(p_2^+) - f^n(p_1^+) = \frac{\sum_{d,t,s} \beta_{dt,ds}^n \left( (p_1^+)^2 - (p_2^+)^2 \right)}{2} + \sum_{d,t} \alpha_{dt}^n (p_1^+ - p_2^+)
\]

\[
= (p_1^+ - p_2^+) \left[ \sum_{d,t} \alpha_{dt}^n + \sum_{d,t,s} \beta_{dt,ds}^n \frac{p_1^+ + p_2^+}{2} \right]
\]

\[
= (p_1^+ - p_2^+) \sum_{d,t} \sum_s x_{dt}^n \left( \frac{p_1^+ + p_2^+}{2} \right).
\]

Since \( \alpha_{dt}^n > 0 \) for all \( n,d,t \) and \( \sum_{n,d,t,s} \beta_{dt,ds}^n < 0 \), we have \( p_1^+ - p_2^+ \geq 0 \) and \( p_1^+ + p_2^+ \geq 0 \). Furthermore, because \( x_{dt}^n > 0 \), \( f^n(p_2^+) - f^n(p_1^+) \geq 0 \), \( \forall n \). Thus, the consumer surplus is higher under \( p_2^+ \). Therefore, under perfect competition, all retailers use \( p_2^+ \) at the equilibrium. This completes the proof of case (a).

Second, in the TOU tariff, we have \( p_{dt}^+ = p_{dt}^m \) for \( d,t \in T_m \) and \( m = 1, \ldots, M \). Then, the equilibrium price is set to recover the total marginal cost of supply in each period, and is described by:

\[
p_m^+ = \frac{\sum_{n,d,t \in T_m} w_{dt} x_{dt}^n(p^+) - A^*_F N |T_m|}{\sum_{n,d,t \in T_m} x_{dt}^n(p^+)} \cdot \frac{DT}{p^+}, \quad \text{for all } m,
\]

where it is assumed that in each period, the retailer receives a portion of the fixed fee, \( A^*_F N \), proportional to the number of hours in that period, i.e., \( |T_m| \). Substituting the consumer demand equations from (EC.7), we obtain

\[
\sum_{n,d,t \in T_m} p_m^+ \sum_s \beta_{dt,ds}^n p_{ds} + \sum_{n,d,t \in T_m} \left( \alpha_{dt}^n p_m^* - \sum_{s \in T_d} w_{dt} \beta_{dt,d,s}^n p_{ds} \right) - \sum_{n,d,t \in T_m} w_{dt} \alpha_{dt}^n + \frac{A^*_F |T_m|}{DT} N = 0.
\]
Rearranging the terms, we get
\[
\sum_{n, dt \in T_m} \left\{ p_m^+ \sum_s \beta_{dt, ds}^n p_d^+ + \epsilon_{dt}^n p_m^+ - \sum_s w_{dt} \beta_{dt, ds}^n p_d^+ - w_{dt} \alpha_{dt}^n + \frac{A_T}{DT} \right\} = 0.
\]

Then, we rewrite the equation above as
\[
\sum_{n, dt \in T_m} \left\{ p_m^+ \left( \sum_{k=1}^M \sum_{s \in T^d_k} \beta_{dt, ds}^n p_k^+ \right) + p_m^+ \alpha_{dt}^n - \left( \sum_{k=1}^M \sum_{s \in T^d_k} w_{dt} \beta_{dt, ds}^n p_k^+ \right) - w_{dt} \alpha_{dt}^n + \frac{A_T}{DT} \right\} = 0. \text{ for all } m.
\]

This completes the proof of case (b).

Finally, there is no fixed fee under RTP. Furthermore, due to marginal cost pricing we pass down the wholesale prices directly onto the consumers. Therefore, in equilibrium, we have \( p_{dt}^* = w_{dt} \) for all \( d, t \). □

Appendix EC.2: Theoretical Results

**Proposition EC.3.** In the social planner’s problem:

(a) Under the optimal TOU tariff and RTP, the total consumptions in each period \( T_m, m = 1, \ldots, M \), are the same.

(b) Under the optimal flat rate, TOU tariff, and RTP, the total annual consumptions are the same.

**Proof.** (a) It follows from Equation (3), and matrix \( B_n \) in Appendix D, that the consumption in any given period \( T_m \) under the optimal TOU tariff, can be written as
\[
\sum_{n, dt \in T_m^d} x_{dt}^n(p_1^*, \ldots, p_M^*) = \sum_{n, dt \in T_m^d} \alpha_{dt}^n + \sum_{n, dt \in T_m^d} \left( \sum_{k=1}^M \sum_{s \in T^d_k} \beta_{dt, ds}^n p_k^+ \right).
\]

By Proposition EC.1, the optimal TOU rate \( p_m^* \) solves the following:
\[
\sum_{n, dt} w_{dt} \left( \sum_{s \in T_m^d} \beta_{dt, ds}^n \right) = \sum_{k=1}^M p_k^+ \left( \sum_{n, dt \in T_m} \sum_{s \in T^d_k} \beta_{dt, ds}^n \right) \quad \text{for all } m.
\]

By rearranging the terms, we get
\[
\sum_{n, dt} w_{dt} \left( \sum_{s \in T_m^d} \beta_{dt, ds}^n \right) = \sum_{n, dt \in T_m^d} \left( \sum_{k=1}^M \sum_{s \in T^d_k} \beta_{dt, ds}^n p_k^+ \right) \quad \text{for all } m.
\]

Then, the consumption in any given period \( T_m \) under the optimal TOU tariff can equivalently be written as
\[
\sum_{n, dt \in T_m^d} x_{dt}^n(p_1^*, \ldots, p_M^*) = \sum_{n, dt \in T_m^d} \alpha_{dt}^n + \sum_{n, dt} w_{dt} \left( \sum_{s \in T_m^d} \beta_{dt, ds}^n \right). \tag{EC.8}
\]

Since \( B_n \) is symmetric, we have
\[
\sum_{n, dt} w_{dt} \left( \sum_{s \in T_m} \beta_{dt, ds}^n \right) = \sum_{n, dt \in T_m} \sum_s \beta_{dt, ds}^n w_{ds}.
\]
By substituting the equation above in (EC.8),
\[
\sum_{n,d} \sum_{t \in T_m^d} x_{dt}^n(p_1^*, \ldots, p_M^*) = \sum_{n,d} \sum_{t \in T_m^d} \alpha_{dt}^n + \sum_{n,d} \sum_{s} \sum_{t \in T_m^d} \beta_{dt,ds}^n w_{ds} = \sum_{n,d} \sum_{t \in T_m^d} x_{dt}^n(w).
\]
This proves that the consumption in each period is the same under TOU tariff and RTP.

(b) It is immediate from part (a) that the consumptions under RTP and the optimal TOU tariff are the same in each period. Thus, the annual consumption is the same under both tariffs. It suffices to show that the annual consumption under the optimal flat rate is the same as that of RTP. It follows from equation (3) that the annual consumption under the optimal flat rate is given by
\[
\sum_{n} x^n(p^*) = \sum_{n,d,t} \alpha_{dt}^n + \sum_{n,d,t} \beta_{dt}^n p^* + \sum_{|t-s| \leq 2} \theta_{t-s} (p^* - p^*) = \sum_{n,d,t} (\alpha_{dt}^n + \beta_{dt}^n p^*).
\]

Then, substituting the optimal flat rate \( p^* \) from Proposition EC.1, we find the total consumption under the flat rate as
\[
\sum_{n} x^n(p^*) = \sum_{n,d,t} \alpha_{dt}^n + \sum_{n,d,t} \sum_{s} \beta_{dt}^n w_{dt} \beta_{dt}^n = \sum_{n,d,t} (\alpha_{dt}^n + w_{dt} \beta_{dt}^n).
\]

Since \( \beta_{dt}^n = \sum_s \beta_{dt,ds}^n \), it follows that
\[
\sum_{n} x^n(p^*) = \sum_{n,d,t} \alpha_{dt}^n + \sum_{n,d,t} \sum_{s} \beta_{dt,ds}^n w_{ds}.
\]

Since \( B_n \) is symmetric, we have
\[
\sum_{n,d,t} \sum_{s} \beta_{dt,ds}^n w_{ds} = \sum_{n,d,t} \sum_{s} \beta_{dt,ds}^n w_{ds}.
\]

Substituting this in equation (EC.9), we find that
\[
\sum_{n} x^n(p^*) = \sum_{n,d,t} \left( \alpha_{dt}^n + \sum_{s} \beta_{dt,ds}^n w_{ds} \right) = \sum_{n} (\alpha^n + B_n w) = \sum_{n} x^n(w).
\]

This proves that the annual consumption under the optimal flat rate and optimal RTP are the same.

**Proposition EC.4.** The flat rate under perfect competition is equal to the social planner’s optimal flat rate if the fixed subscription fee under perfect competition is equal to the optimal fixed fee under the social planner setting.

**Proof.** Suppose the social planner charges the optimal flat-rate tariff \((p^*, A_F^*)\) given in Proposition EC.1. Plugging \((p^*, A_F^*)\) into (EC.1) gives
\[
A_F^* = \frac{\sum_{n,d,t} w_{dt} x_{dt}^n(p^*) - \sum_{n,d,t} p^* x_{dt}^n(p^*)}{N}.
\]
We know from equation (EC.6) that conditional on charging the social planner’s optimal fixed fee, the flat rate under perfect competition is

$$p^+ = \frac{\sum_{n,d,t} w_{dt} x_{dt}^n(p^+) - A_F N}{\sum_{n,d,t} x_{dt}^n(p^+)}. \tag{EC.6}$$

Plugging in $A_F$: as given above, we obtain

$$p^+ = \frac{\sum_{n,d,t} w_{dt} x_{dt}^n(p^+) - \sum_{n,d,t} w_{dt} x_{dt}^n(p^*) + \sum_{n,d,t} p^* x_{dt}^n(p^*)}{\sum_{n,d,t} x_{dt}^n(p^+)}. \tag{EC.7}$$

Substituting $x_{dt}^n(p^+)$ and $x_{dt}^n(p^*)$ from equation (3) gives

$$p^+ = \frac{\sum_{n,d,t} w_{dt} (\alpha^{n}_{dt} + \beta^{n}_{dt} p^+) - \sum_{n,d,t} w_{dt} (\alpha^{n}_{dt} + \beta^{n}_{dt} p^*) + \sum_{n,d,t} p^* (\alpha^{n}_{dt} + \beta^{n}_{dt} p^*)}{\sum_{n,d,t} (\alpha^{n}_{dt} + \beta^{n}_{dt} p^+)}.$$

Rearranging the terms gives

$$\left(p^+ - p^*\right) \sum_{n,d,t} \left(\beta^{n}_{dt} (p^+ + p^*) + \alpha^{n}_{dt} - w_{dt} \beta^{n}_{dt}\right) = 0, \tag{EC.10}$$

where

$$\sum_{n,d,t} \left(\beta^{n}_{dt} (p^+ + p^*) + \alpha^{n}_{dt} - w_{dt} \beta^{n}_{dt}\right) = \sum_{n,d,t} (\alpha^{n}_{dt} + \beta^{n}_{dt} p^+) + \sum_{n,d,t} (\alpha^{n}_{dt} + \beta^{n}_{dt} p^*) - \sum_{n,d,t} (\alpha^{n}_{dt} + \beta^{n}_{dt} w_{dt}) = \sum_{n} x^n(p^+) + \sum_{n} x^n(p^*) - \sum_{n} x^n(w).$$

By Proposition EC.3, we have $\sum_{n} x^n(p^*) = \sum_{n} x^n(w)$. Therefore,

$$\sum_{n,d,t} \left(\beta^{n}_{dt} (p^+ + p^*) + \alpha^{n}_{dt} - w_{dt} \beta^{n}_{dt}\right) = \sum_{n} x^n(p^+).$$

Plugging this into (EC.10) gives

$$\left(p^+ - p^*\right) \sum_{n} x^n(p^+) = 0.$$

Since $\sum_{n} x^n(p^+) > 0$, this equality only holds if $p^+ = p^*$, i.e., the flat rate under perfect competition is equal to the social planner’s optimal flat rate. \(\square\)

**Appendix EC.3: Choice of Temperature as an Explanatory Variable**

The seasonality in consumption is clearly visible in Figure 1. Therefore, we want to include a variable to control for the climate effects on consumption. The possible candidate variables are the temperature, and sunlight duration, given the household electricity consumption habits in Ireland. In a research paper looking at household electrical appliance usage in Ireland, Economic and Social Research Institute (ESRI) (2012) reports that main categories of household electricity demand are water heating (23%), lighting (18%), space heating (14%), and cooking (12%). Refrigeration accounts for 11% of household demand while wet appliances such as washing machines account for 9%. Small appliances and entertainment devices account for 13%. We expect that the electricity consumption for lightning is correlated with daily sunlight duration, and the consumption for heating purposes is correlated with temperature.

We look at the hourly temperature (°C) and daily sunlight duration (hours rounded to 1 decimal point) recorded at the Dublin International Airport to capture these climate effects. Temperature
ranges between -10.5 and 23, with a standard deviation of 6.3. Daily sunshine duration ranges between 0 and 15.8, with a standard deviation of 3.8. We consider the impact of including either of these variables in our consumer demand equation in (3). For representing the temperature, we include $\alpha_{\text{temp}}$ as a modifier to the intercept parameter $\alpha_{d}^{n}$ to explain the variable $\text{temp}_{dt}$ (the temperature (in Celsius) for day $d$, hour $t$). For representing the sunlight duration, we include $\alpha_{\text{sunlight}}$ as a modifier to the intercept parameter $\alpha_{d}^{n}$ to explain the variable $\text{sunlight}_{d}$ (sunlight duration for day $d$).

Our variable of choice for the model is the hourly temperature, $\text{temp}_{dt}$. We compare the explanatory power gained from including either of these two variables in our regression model. We notice that including temperature vs. sunlight duration in the model as an explanatory variable does not have a significant impact on the estimates for the other model parameters. At the first glance, we observe that by itself sunlight duration explains hourly consumption slightly better than temperature. There is 5% correlation between sunlight duration and hourly consumption, in comparison to the 4% with hourly temperature.

However, in conjunction with the seasonality variables in our model, the hourly temperature adds more explanatory power to the model. When these variables are included in the model together, we also see that both of them are significant, although temperature is more significant with a tighter confidence interval. When sunlight duration is included in the regression model itself (along with other independent variables), we achieve a 0.1% increase in model fit. On the other hand, when temperature is included, we achieve a 0.9% increase. Finally, when the two are added together, we see a 1% increase in model fit. Therefore, we conclude that temperature adds more information to the model than sunlight duration, and choose to include only the temperature variable, in order to balance between additional explanatory power and over-fitting.

**Appendix EC.4: Load-Dependent Wholesale Prices**

In our paper, we assume wholesale prices are exogenous to the retail pricing problem. This section tests the robustness of the results to this assumption. In what follows, we allow the wholesale prices to depend on the aggregate residential demand, i.e., $w_{dt} = w_{dt}(X_{dt})$. Here $X_{dt}$ represents the aggregate residential load on day $d$ and hour $t$, such that $X_{dt} = \sum_{n} x_{dt}^{n}$, where $x_{dt}^{n}$ is the electricity consumption of household $n$ on day $d$, hour $t$, as given in Equation (3).

**Figure EC.1** Scatter-plot of wholesale prices and the system load for the years 2009-2012.

We assume for simplicity that the wholesale price is a linear function of the aggregate load, and we use the hourly wholesale price and the system load data for 2009-2012 to determine the parameters of this function\(^{30}\). Figure EC.1 shows that prices vary similarly with system load across different years so we model the yearly effects as constant shifts, i.e., by incorporating a fixed-effect

\(^{30}\)The aggregate residential load is assumed to be a constant fraction of the total system load at all hours.
term for each year. Contrary to the year effects, the relationship between prices and the load differs across the seasons within a year, and the hours within a day. Therefore, we let indicator variables for the seasonal and hourly effects to interact with the system load. To be specific, we assume:

$$w_{ydt}(X_{ydt}) = \eta^0_{ydt} + \eta_{dt}X_{ydt} + \xi_{ydt}, \quad (EC.11)$$

where the error terms $\xi_{ydt}$ have zero mean, are homoskedastic, and $E[\xi_{ydt}|X_{ydt}] = 0$. We estimate parameters $\eta^0_{ydt}$ and $\eta_{dt}$ using the system load and wholesale price data from 2009 to 2012, and the indices $y \in \{2009, 2010, 2011, 2012\}$, $d \in \{1, \ldots, 365\}$ and $t \in \{1, \ldots, 24\}$ represents years, days of the given year, and the hours of the given day, respectively. In Equation (EC.11), the parameter $\eta^0_{ydt}$ is a linear function of several indicator variables: $S_d$ takes the value “1” if day $d$ is in season $S$ and “0” otherwise, for all $S \in \{summer, winter, Christmas\}$; $H_t$ is the indicator variable for hour $H$ of the day for all $H \in \{1, \ldots, 24\}$ and $Y_y$ is the indicator variable for year $Y$ for all $Y \in \{2009, 2010, 2011, 2012\}$. We also include indicator variables for all possible interactions among $S_d$, $H_t$, and $Y_y$. Similarly, $\eta_{dt}$ is a linear function of: $S_d$, $H_t$ and their interactions where $S \in \{summer, winter, Christmas\}$, and $H \in \{1, \ldots, 24\}$.

### EC.4.1. Social Planner’s Problem with Load-dependent Wholesale Prices

The social planner chooses a two-part tariff with a variable price $p^*_{dt}$ and a fixed fee $A^*$. For the proofs and calculations from this point on, we only use the wholesale prices and observations for the year 2010, and therefore we omit the index $y$ representing the years. The wholesale prices $w_{dt}$ are defined as in Equation (EC.11), where $y = 2010$, and the coefficients are set at their 2010 values. That is, restricting attention to year 2010, we have that:

$$w_{dt} = \eta^0_{dt} + \eta_{dt}X_{dt} + \xi_{dt}, \quad (EC.12)$$

where $\eta^0_{dt} = \eta^0_{2010,dt}$ and $\xi_{dt} = \xi_{2010,dt}$.

The social planner solves the problem in (2), but given the random nature of wholesale prices, she substitutes $E[w_{dt}]$ in place of $w_{dt}$ in the budget constraint. Specifically, she solves:

$$\max_{(p,\Lambda)} \sum_n \left(u^n(x^n) - \sum_{d} \sum_{t} p_{dt} x^n_{dt} \right) - AN$$

subject to

$$AN + \sum_n \sum_{d} \sum_{t} p_{dt} x^n_{dt} \geq \sum_n \sum_{d} \sum_{t} E[w_{dt}] x^n_{dt}. \quad \text{PROP. EC.5.}$$

The optimal two-part tariffs under the social welfare maximization for each of the three pricing schemes are:

(a) The optimal flat rate:

$$p^* = \frac{\sum_{d,t} (\sum_{n,s} \beta_{dt,ds}) [\eta^0_{dt} + 2\eta_{dt}(\sum_{n} \alpha^n_{ds})]}{\sum_{d,t} (\sum_{n,s} \beta^n_{dt,ds}) [1 - 2\eta_{dt}(\sum_{n,s} \beta^n_{dt,ds})]}.$$  

(b) The optimal TOU tariff: For all $m = 1, \ldots, M$, $p^*_m$ jointly solve the following $M$ equations:

$$\sum_k^{M} p_k \sum_{d,t \in T_m} \sum_{s \in T_k} \beta_{dt,ds} - \sum_k^{M} p_k \left[ \sum_{d,t} \eta_{dt} \left( \sum_{s \in T_m} \beta_{dt,ds} \right) \left( \sum_{s \in T_k} \beta_{dt,ds} \right) \right] = \sum_{d,t} \sum_{s \in T_m} \tilde{\beta}_{dt,ds} (\eta^0_{dt} + 2\eta_{dt} \tilde{\alpha}_{dt}).$$

(c) The optimal RTP: For all $d,t$, optimal prices $p^*_{dt}$ jointly solve the following $|DT|$ equations:

$$p^*_{dt} - 2\eta_{dt} \left( \sum_{s \in T_d} \tilde{\beta}_{dt,ds} p^*_{ds} \right) = \eta^0_{dt} + 2\eta_{dt} \tilde{\alpha}_{dt}, \forall d,t.$$

In all pricing schemes, the optimal fixed fee $A^*$ can be found by plugging in the optimal prices into the budget constraint.

---

31 A similar analysis can be done for perfect competition, but we focus only on the social planner for illustration purposes.
Proof: It is easy to see that the budget constraint of the social planner’s problem binds under the optimal solution. That is,

\[ AN = \sum_n \sum_d \sum_t \mathbb{E}[w_{dt}] x^n_{dt} - \sum_n \sum_d \sum_t p_{dt} x^n_{dt}. \]

Substituting this into the objective function leads to the following unconstrained optimization problem:

\[
\max_p \sum_n \left( u^n(x^n) - \sum_d \sum_t \mathbb{E}[w_{dt}] x^n_{dt} \right)
\]

Then, substituting the households’ utility function in (5), we arrive at the problem of maximizing:

\[
\sum_n \left( \frac{1}{2} (x^n - \alpha^n)^T B_n^{-1} (x^n - \alpha^n) - \sum_d \sum_t \mathbb{E}[w_{dt}] x^n_{dt} \right)
\]

which can equivalently be written without loss of optimality as:

\[
\sum_n \left( \frac{1}{2} (x^n - \alpha^n)^T B_n^{-1} (x^n - \alpha^n) - \sum_d \sum_t \mathbb{E}[w_{dt}] x^n_{dt} \right)
\]

We know from Equation (7) that \( x^n = \alpha^n + B_n p \). Then, also using (EC.12), the above equation becomes:

\[
\sum_n \left( \frac{1}{2} (x^n - \alpha^n)^T B_n^{-1} (x^n - \alpha^n) - \sum_d \sum_t \mathbb{E}[w_{dt}] x^n_{dt} \right)
\]

Let \( \beta^n_{dt,ds} \neq 0 \) define the parameters of \( B_n \) as in (6), and let \( T_t \) define the set of hours \( s \) for which \( \beta^n_{dt,ds} \neq 0 \) (there is a substitution between hours \( t \) and \( s \)). Then, the aggregate residential demand \( X_{dt} \) observed by the retailers in day \( d \), hour \( t \) is written as:

\[
X_{dt} = \sum_n x^n_{dt} = \sum_n \alpha^n_{dt} + \sum_{n,s \in T_t} \beta^n_{dt,ds} p_{ds} = \bar{\alpha}_{dt} + \sum_{s \in T_t} \bar{\beta}_{dt,ds} p_{ds}
\]

where \( \bar{\alpha}_{dt} = \sum_n \alpha^n_{dt} \), and \( \bar{\beta}_{dt,ds} = \sum_n \beta^n_{dt,ds} \). Substituting these in, the social planner’s objective function becomes:

\[
\sum_{d,t} \left\{ \frac{1}{2} p_{dt} \left( \sum_s \bar{\beta}_{dt,ds} p_{ds} \right) - \eta^0_{dt} \left( \bar{\alpha}_{dt} + \sum_s \bar{\beta}_{dt,ds} p_{ds} \right) - \eta_{dt} \left( \bar{\alpha}_{dt} + \sum_s \bar{\beta}_{dt,ds} p_{ds} \right)^2 \right\}
\]

\[
= \sum_{d,t} \left\{ -\eta^0_{dt} \bar{\alpha}_{dt} - \eta_{dt} (\bar{\alpha}_{dt})^2 + \left( \sum_s \bar{\beta}_{dt,ds} p_{ds} \right) \left[ \frac{p_{dt}}{2} - \eta^0_{dt} - 2 \eta_{dt} \bar{\alpha}_{dt} - \eta_{dt} \left( \sum_s \bar{\beta}_{dt,ds} p_{ds} \right) \right] \right\}
\]

Omitting the terms that do not depend on price, the social planner equivalently solves:

\[
\max_p \sum_{d,t} \left( \sum_s \tilde{\beta}_{dt,ds} p_{ds} \right) \left[ \frac{p_{dt}}{2} - \eta^0_{dt} - 2 \eta_{dt} \bar{\alpha}_{dt} - \eta_{dt} \left( \sum_s \tilde{\beta}_{dt,ds} p_{ds} \right) \right]
\]

(EC.13)

The price terms have a highest degree of 2 in the objective function, with coefficient \( \sum_{d,t,s} \tilde{\beta}_{dt,ds} < 0 \); and hence, the objective function is concave. Thus, studying the first-order conditions gives us the desired results, which we do next for each of the three cases of interest.
First, under the flat rate, \( p_{dt} = p \) for all \( d, t \), and the social planner’s objective function becomes:

\[
p^2 \sum_{d,t} \left( \sum_{s} \beta_{dt,ds} \right) \left[ 1/2 - \eta_{dt} \left( \sum_{s} \tilde{\beta}_{dt,ds} \right) \right] - p \sum_{d,t} \left( \sum_{s} \tilde{\beta}_{dt,ds} \right) \left[ \eta_{dt}^0 + 2 \eta_{dt} \tilde{\alpha}_{dt} \right].
\]

The corresponding first-order condition gives:

\[
p^* = \frac{\sum_{d,t} \left( \sum_{s} \tilde{\beta}_{dt,ds} \right) \left( \eta_{dt}^0 + 2 \eta_{dt} \tilde{\alpha}_{dt} \right)}{\sum_{d,t} \left( \sum_{s} \tilde{\beta}_{dt,ds} \right) \left[ 1 - 2 \eta_{dt} \left( \sum_{s} \tilde{\beta}_{dt,ds} \right) \right]}.
\]

Substituting this optimal price into the budget constraint determines the optimal fixed fee, and completes the proof of case (a).

Second, we consider the TOU tariff. In this case, \( p_{dt} = p_m \) for \( d, t \in T_m \) and \( m = 1, \ldots, M \). Thus, the problem becomes:

\[
\max_{p_m} \sum_{m=1}^{M} \sum_{d,t} \left\{ \left[ \frac{p_m}{2} - \eta_{dt}^0 - 2 \eta_{dt} \tilde{\alpha}_{dt} - \eta_{dt} \left( \sum_{k=1}^{M} \sum_{s \in T_k} \tilde{\beta}_{dt,ds} p_k \right) \right] \right\}.
\]

Then, for each \( m = 1, \ldots, M \), the first order conditions can be jointly written as a system of \( M \) equations:

\[
\sum_{k=1}^{M} \sum_{d,t} \sum_{s \in T_k} \tilde{\beta}_{dt,ds} - 2 \sum_{k=1}^{M} \sum_{d,t} \eta_{dt} \left( \sum_{s \in T_m} \tilde{\beta}_{dt,ds} \right) \left( \sum_{s \in T_k} \tilde{\beta}_{dt,ds} \right) = \sum_{d,t} \sum_{s \in T_m} \tilde{\beta}_{dt,ds} \left( \eta_{dt}^0 + 2 \eta_{dt} \tilde{\alpha}_{dt} \right).
\]

There are \( M \) independent equations with \( M \) unknowns, so we can solve for each optimal period price \( p^*_m \). Substituting these into the budget constraint determines the optimal fixed fee, and completes the proof of case (b).

Lastly, for RTP, we look at the first-order conditions for the problem defined in (EC.13). Then, proceeding as above, the partial derivative for the social planner’s problem for each period \( d, t \) becomes:

\[
0 = \sum_{s \in T_t} \tilde{\beta}_{dt,ds} p_d - \sum_{s \in T_t} \tilde{\beta}_{dt,ds} \eta_{ds} - 2 \eta_{ds} \tilde{\alpha}_{ds} - \sum_{s \in T_t} 2 \tilde{\beta}_{dt,ds} \eta_{ds} \left( \sum_{u \in T_s} \tilde{\beta}_{ds,du} p_d \right)
\]

Grouping the terms, we get:

\[
0 = \sum_{s \in T_t} \tilde{\beta}_{dt,ds} \left[ p_d - \eta_{ds}^0 - 2 \eta_{ds} \tilde{\alpha}_{ds} - 2 \eta_{ds} \left( \sum_{u \in T_s} \tilde{\beta}_{ds,du} p_d \right) \right]
\]

Given that these equations hold for all periods and prices, the term inside square brackets have to be zero for all periods. Hence, for all \( d, t \), we have:

\[
0 = p_{dt} - \eta_{dt}^0 - 2 \eta_{dt} \tilde{\alpha}_{dt} - 2 \eta_{dt} \left( \sum_{s \in T_t} \tilde{\beta}_{dt,ds} p_d \right)
\]

There are \( DT \) independent equations with \( DT \) unknowns, and we can solve these equations jointly to find the price in each period. Again, substituting these prices into the budget constraint determines the optimal fixed fee, and completes the proof of case (c). □
EC.4.2. Prices and Consumption under Load-dependent Wholesale Prices

To check the robustness of our results to the exogenous wholesale prices assumption, we repeat the analysis in Section 6. We start by characterizing the relationship between the system load and the wholesale price, i.e., we find the coefficients for equation (EC.12). We observe in Figure EC.1 that there are several outliers, i.e., hours during which the wholesale price is significantly higher than usual. Incorporating such outliers in a parsimonious model is difficult because the wholesale price can spike in practice due to many different operational reasons such as unexpected outages, congestion in transmission lines, fuel shortages, etc. For example, during the polar vortex in January 2014 in the U.S., the regional transmission organizations experienced very high prices due to extreme demand, fuel delivery problems and unplanned shutdowns of generators. Capturing these potential shocks to the wholesale electricity price requires a more complex model, which can only be solved numerically. However, this is beyond the scope of our research. We simply want to look at the average relationship between the price and the system load, for which a simple model suffices. A potential risk of using a simple linear model is that the results might be influenced by the outlying observations. Therefore, we run three analyses where we remove 1%, 3% and 5% of the outlying observations, as shown in Figure EC.2.

In each outlier-removed analysis, we first run a linear regression to calculate $\eta_0$ and $\eta_d$ in (EC.12). Using these estimates together with the $\alpha_{\text{d}}$ and $\beta_{\text{d},\text{s}}$ parameters of the consumer demand in (3), and we find the optimal retail rates under the social planner as described in Proposition EC.5. These optimal flat rate and the TOU tariffs are given in Table EC.1.

We next calculate in Table EC.2 the changes in the peak, off-peak and total loads under the optimal TOU tariffs and RTP compared to the flat rate. Table EC.3 further refines this comparison for the peak load in each season.

Although slightly different in magnitude, these results are directionally very similar to the counterfactual results presented in Section 6, and the same conclusions continue to hold. Like before, there is no change to total consumption under time-based tariffs, and the annual peak load changes roughly by the same amount under all price tariffs. The annual TOU tariff performs as well as the more flexible seasonal TOU tariff and the RTP in terms of the annual peak load reduction. However, the more flexible tariffs are better at reducing the Christmas peak load, when the peak load reduction is the most valuable.
Table EC.1  Optimal retail rates for the social planner under load-dependent wholesale prices.

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</thead>
<tbody>
<tr>
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<td>Day</td>
<td>Peak</td>
<td>Night</td>
<td>Day</td>
<td>Peak</td>
</tr>
<tr>
<td>Flat</td>
<td>12.5</td>
<td>12.5</td>
<td>12.5</td>
<td>12.3</td>
<td>12.3</td>
<td>12.3</td>
</tr>
<tr>
<td>Annual TOU</td>
<td>10.7</td>
<td>14.9</td>
<td>29.5</td>
<td>10.6</td>
<td>14.7</td>
<td>26.4</td>
</tr>
<tr>
<td>Seasonal TOU</td>
<td>Summer</td>
<td>10.7</td>
<td>15.4</td>
<td>18.4</td>
<td>10.7</td>
<td>15.1</td>
</tr>
<tr>
<td></td>
<td>Winter</td>
<td>10.2</td>
<td>13.8</td>
<td>37.9</td>
<td>10.2</td>
<td>13.7</td>
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<tr>
<td></td>
<td>Christmas</td>
<td>12.8</td>
<td>17.2</td>
<td>49.7</td>
<td>12.5</td>
<td>17.1</td>
</tr>
</tbody>
</table>

The prices are given in 2010 €. The retail rates are in cents/kWh. Fixed fees are not reported as they are a fixed transfer of wealth, and they have no impact on consumption. The results are shown for three cases where 1%, 3% or 5% of the observations are removed as outliers; see Figure EC.2.

Table EC.2  The impact of optimal TOU tariffs and RTP on the peak, off-peak and total loads.

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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Peak</td>
<td>Off-Peak</td>
<td>Total</td>
<td>Peak</td>
<td>Off-Peak</td>
<td>Total</td>
</tr>
<tr>
<td>Annual TOU</td>
<td>-3.7%</td>
<td>0.6%</td>
<td>0.0%</td>
<td>-3.0%</td>
<td>0.5%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Seasonal TOU</td>
<td>-3.6%</td>
<td>0.6%</td>
<td>0.0%</td>
<td>-3.0%</td>
<td>0.5%</td>
<td>0.0%</td>
</tr>
<tr>
<td>RTP</td>
<td>-3.6%</td>
<td>0.6%</td>
<td>0.0%</td>
<td>-2.9%</td>
<td>0.5%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

The percentage change in the the peak, off-peak and total loads under annual TOU tariff, seasonal TOU tariff and RTP compared to the flat rate under the social planner. The results are shown for three cases where 1%, 3% or 5% of the observations are removed as outliers; see Figure EC.2.

Table EC.3  Comparison of seasonal peak load reduction under the load-dependent wholesale prices.

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<th>3% Removed</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Annual TOU</td>
<td>-4.5%</td>
<td>-3.2%</td>
<td>-2.6%</td>
<td>-3.7%</td>
<td>-3.7%</td>
<td>-2.6%</td>
<td>-2.1%</td>
<td>-3.0%</td>
<td>-3.3%</td>
</tr>
<tr>
<td>Seasonal TOU</td>
<td>-1.3%</td>
<td>-5.0%</td>
<td>-5.7%</td>
<td>-3.6%</td>
<td>-1.2%</td>
<td>-4.2%</td>
<td>-4.0%</td>
<td>-3.0%</td>
<td>-1.3%</td>
</tr>
<tr>
<td>RTP</td>
<td>-1.3%</td>
<td>-5.0%</td>
<td>-5.6%</td>
<td>-3.6%</td>
<td>-1.2%</td>
<td>-4.2%</td>
<td>-3.9%</td>
<td>-2.9%</td>
<td>-1.3%</td>
</tr>
</tbody>
</table>

The percentage change in the peak load by season with annual TOU, seasonal TOU tariff and RTP compared to the flat rate under the social planner. The results are shown for three cases where 1%, 3% or 5% of the observations are removed as outliers; see Figure EC.2.

Appendix EC.5: Perfectly Competitive Equilibrium without the Fixed Fee

In our counterfactual analysis, we assume that retailers in a perfectly competitive equilibrium recover part of their costs by using a fixed fee that is equal to that of the social planner. However, under the traditional perfect competition setting, the retailers directly price at the marginal cost and do not charge a fixed cost, i.e., \( p^+ = w \) and \( A^+ = 0 \). In this section, we analyze such an equilibrium.
PROPOSITION EC.6. Under the perfectly competitive equilibrium characterized by marginal cost pricing:

(a) The optimal flat rate, $p^+$, solves a quadratic equation and is given by:

$$p^+ = \sqrt{\left[\sum_{n,d,t} \left(\alpha_{dt}^n - \sum_s w_{dt} \beta_{dt,ds}^n\right)\right]^2 + 4\left(\sum_{n,d,t,s} \beta_{dt,ds}^n \left(\alpha_{dt}^n \sum_{n,d,t} w_{dt} \alpha_{dt}^n\right) - \sum_{n,d,t} \left(\alpha_{dt}^n - \sum_s \beta_{dt,ds}^n\right)\right)} \over 2\left(\sum_{n,d,t,s} \beta_{dt,ds}^n\right) \quad (EC.14)$$

(b) The optimal TOU prices, $p_n^+$, satisfy:

$$\sum_{n,d,t \in T_m} \left\{p_m^+ \left(\sum_{k=1}^M \sum_{s \in T_k} \beta_{dt,ds}^n P_k^\ast\right) + p_m^+ \alpha_{dt}^n - \left(\sum_{k=1}^M \sum_{s \in T_k} w_{dt} \beta_{dt,ds}^n P_k^\ast\right) - w_{dt} \alpha_{dt}^n\right\} = 0 \quad \text{for all } m,$$

(c) The optimal real-time prices are $p_{dt}^n = w_{dt}, \forall d, t$.

**Proof.** First, consider the flat-rate pricing, i.e., $p_{dt} = p$ for all $d, t$. Under this pricing scheme, all hours in the year are priced uniformly, and the marginal cost of supplying electricity over the whole year is given by the load-weighted average of wholesale prices in the whole year. Therefore, the flat rate in a perfectly competitive equilibrium is found by:

$$p^+ = \frac{\sum_{n,d,t} w_{dt} x_{dt}^n (p^+) \sum_{n,d,t} x_{dt}^n (p^+)}{\sum_{n,d,t} x_{dt}^n (p^+)} \quad (EC.15)$$

Note that this variable rate is exactly equal to the marginal cost, and allows retailers to cover all of their costs. Therefore, in equilibrium, the fixed fee $A^+$ equals 0. Let $\beta_{dt,ds}^n \neq 0$ define the price-sensitivity parameters $\beta_{dt,ds}^n$, $\theta_1$ and $\theta_2$ as in (6), and for each hour $t$, define $T_t$ as the set of hours $s$ for which $\beta_{dt,ds}^n \neq 0$. Then, the household demand equation given in (3) can be equivalently written as in (EC.7). Substituting this in (EC.15), and rearranging the terms, we find that $p^+$ solves the following quadratic equation:

$$0 = p^+ \sum_{n,d,t} x_{dt}^n (p^+) - \sum_{n,d,t} w_{dt} x_{dt}^n (p^+)$$

$$= p^+ \sum_{n,d,t} \left(\alpha_{dt}^n + \sum_{s \in T_t} \beta_{dt,ds}^n p^+\right) - \sum_{n,d,t} w_{dt} \left(\alpha_{dt}^n + \sum_{s \in T_t} \beta_{dt,ds}^n p^+\right)$$

$$= (p^+)^2 \sum_{n,d,t,s \in T_t} \beta_{dt,ds}^n + p^+ \sum_{n,d,t} \left(\alpha_{dt}^n - \sum_{s \in T_t} w_{dt} \beta_{dt,ds}^n\right) - \sum_{n,d,t} w_{dt} \alpha_{dt}^n = 0.$$

This quadratic equation has the following roots:

$$p_1^+ = \frac{-\sqrt{\left[\sum_{n,d,t} \left(\alpha_{dt}^n - \sum_s w_{dt} \beta_{dt,ds}^n\right)\right]^2 + 4\left(\sum_{n,d,t,s} \beta_{dt,ds}^n \left(\sum_{n,d,t} w_{dt} \alpha_{dt}^n\right) - \sum_{n,d,t} \left(\alpha_{dt}^n - \sum_s \beta_{dt,ds}^n\right)\right)}}{2\left(\sum_{n,d,t,s} \beta_{dt,ds}^n\right)},$$

$$p_2^+ = \frac{\sqrt{\left[\sum_{n,d,t} \left(\alpha_{dt}^n - \sum_s w_{dt} \beta_{dt,ds}^n\right)\right]^2 + 4\left(\sum_{n,d,t,s} \beta_{dt,ds}^n \left(\sum_{n,d,t} w_{dt} \alpha_{dt}^n\right) - \sum_{n,d,t} \left(\alpha_{dt}^n - \sum_s \beta_{dt,ds}^n\right)\right)}}{2\left(\sum_{n,d,t,s} \beta_{dt,ds}^n\right)}.$$

Similar to the proof in the fixed fee case in Proposition EC.6, among two retailers that offer different flat rate tariffs, consumers would pick the retailer with $p_2^+$, as it gives them a better overall surplus. Since the retailers are under perfect competition, all of the retailers will prefer $p_2^+$ in the equilibrium. This completes the proof of case (a).
Second, in the TOU tariff, we have $p^+_d = p^+_m$ for $d, t \in T_m$ and $m = 1, \ldots, M$. Then, similar to equation (EC.15) in case (a), the equilibrium prices will be set to recover the total marginal costs of supply in each period, and they will be described by:

$$p^+_m = \frac{\sum_{n,d,t \in T_m} w_{dt} x^+_n (p^+)}{\sum_{n,d,t \in T_m} x^+_n (p^+)}, \quad \forall m = 1, \ldots, M.$$ 

Substituting the consumer demand equations, we have:

$$\sum_{n,d,t \in T_m} p^+_m \sum_{s \in T_k} \beta^+_n d_{dt,ds} p^+_s + \sum_{n,d,t \in T_m} \left( \alpha^+_n d_{dt} p^+_m - \sum_{s \in T_k} w_{dt} \beta^+_n d_{dt,ds} p^+_s \right) - \sum_{n,d,t \in T_m} w_{dt} \alpha^+_n d_{dt} = 0.$$ 

Rearranging the terms, we get:

$$\sum_{n,d,t \in T_m} \left\{ p^+_m \sum_{s \in T_k} \beta^+_n d_{dt,ds} p^+_s + \alpha^+_n d_{dt} p^+_m - \sum_{s \in T_k} w_{dt} \beta^+_n d_{dt,ds} p^+_s - w_{dt} \alpha^+_n d_{dt} \right\} = 0.$$ 

Notice that by definition of the TOU tariff, each hour $s$ in the set $T_t$ belongs to one of the pricing periods $T_k$, for $k = \{1, \ldots, M\}$, with $p^+_d = p^+_k$. Then, the above equations can be written as:

$$\sum_{n,d,t \in T_m} \left\{ p^+_m \left( \sum_{k=1}^M \sum_{s \in T_k} \beta^+_n d_{dt,ds} p^+_s \right) + p^+_m \alpha^+_n d_{dt} - \left( \sum_{k=1}^M \sum_{s \in T_k} w_{dt} \beta^+_n d_{dt,ds} p^+_s \right) - w_{dt} \alpha^+_n d_{dt} \right\} = 0.$$ 

We can solve these $M$ equations jointly for the $M$ unknown price variables that we have. This completes the proof of case (b).

Finally, under RTP, marginal cost pricing equals passing down the wholesale prices directly onto the consumers. Therefore, in equilibrium, we have $p^+_d = w_{dt}$ for all $d, t$. □

**Counterfactual Results Under the Perfectly Competitive Equilibrium without the Fixed Fee:** Section 6 presents the numerical results in the perfectly competitive equilibrium under a setting with two-part tariffs. Here, we present the results for an equilibrium with linear tariffs (without fixed fee), in comparison to the social planner’s optimal results, in a similar fashion to Section 6. We find that the earlier results mostly carry over to this case.

| Table EC.4 | Equilibrium retail prices. |
|---|---|---|---|---|---|---|
| | Social Planner | Perfect Competition |
| | Night | Day | Peak | Night | Day | Peak |
| Flat | 12.5 | 12.5 | 12.5 | 14.5 | 14.5 | 14.5 |
| Annual TOU | 11.5 | 14.2 | 18.5 | 11.7 | 14.3 | 19.6 |
| Seasonal TOU | | | | | | |
| Summer | 11.4 | 14.5 | 15.8 | 11.5 | 14.5 | 15.8 |
| Winter | 11.2 | 13.4 | 19.5 | 11.4 | 13.7 | 20.2 |
| Christmas | 13.7 | 15.8 | 28.8 | 13.9 | 16.0 | 29.6 |
| RTP | $w_{dt}$ | $w_{dt}$ | $w_{dt}$ | $w_{dt}$ | $w_{dt}$ | $w_{dt}$ |

Retail rates are in cents/kWh. The annual fixed fee $A$ for the social planner is €115 under flat rate, €17 under the annual TOU tariff, €11 under the seasonal TOU tariff, and 0 under RTP. There is no fixed fee under perfect competition.

Retail prices in equilibrium are presented in Table EC.4, and the impact of these tariffs on annual and seasonal load changes are presented in Tables EC.5 and EC.6. Under perfect competition without the fixed fee, we see that the total consumption slightly increases. However, the results continue to hold directionally. The annual peak load changes roughly by the same amount under all price tariffs. The annual TOU tariff performs as well as the more flexible seasonal TOU tariff.
Table EC.5  The impact of optimal TOU tariffs and RTP on the peak, off-peak and total loads

<table>
<thead>
<tr>
<th></th>
<th>Change in Consumption:</th>
<th>Peak</th>
<th>Off-Peak</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social Planner</td>
<td>Annual TOU</td>
<td>-1.2%</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>Seasonal TOU</td>
<td>-1.2%</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>RTP</td>
<td>-1.2%</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Perfect Competition</td>
<td>Annual TOU</td>
<td>-1.2%</td>
<td>1.4%</td>
<td>1.0%</td>
</tr>
<tr>
<td></td>
<td>Seasonal TOU</td>
<td>-1.0%</td>
<td>1.4%</td>
<td>1.1%</td>
</tr>
<tr>
<td></td>
<td>RTP</td>
<td>-1.0%</td>
<td>1.5%</td>
<td>1.1%</td>
</tr>
</tbody>
</table>

The percentage change with annual TOU, seasonal TOU tariff and RTP compared to the flat rate under the social planner vs. the perfectly competitive setting.

Table EC.6  Comparison of seasonal peak load reduction under equilibrium prices.

<table>
<thead>
<tr>
<th></th>
<th>Summer</th>
<th>Winter</th>
<th>Christmas</th>
<th>Annual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social Planner</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual TOU</td>
<td>-1.5%</td>
<td>-1.1%</td>
<td>-0.8%</td>
<td>-1.2%</td>
</tr>
<tr>
<td>Seasonal TOU</td>
<td>-0.7%</td>
<td>-1.3%</td>
<td>-2.4%</td>
<td>-1.2%</td>
</tr>
<tr>
<td>RTP</td>
<td>-0.7%</td>
<td>-1.3%</td>
<td>-2.4%</td>
<td>-1.2%</td>
</tr>
<tr>
<td>Perfect Competition</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual TOU</td>
<td>-1.5%</td>
<td>-1.1%</td>
<td>-0.8%</td>
<td>-1.2%</td>
</tr>
<tr>
<td>Seasonal TOU</td>
<td>-0.4%</td>
<td>-1.2%</td>
<td>-2.4%</td>
<td>-1.0%</td>
</tr>
<tr>
<td>RTP</td>
<td>-0.4%</td>
<td>-1.1%</td>
<td>-2.2%</td>
<td>-1.0%</td>
</tr>
</tbody>
</table>

The change in peak load by season with annual TOU, seasonal TOU and RTP compared to the flat rate under the social planner versus the perfectly competitive setting.

Table EC.7  Comparison of carbon emissions.

<table>
<thead>
<tr>
<th></th>
<th>Social Planner</th>
<th>Perfect Competition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual TOU</td>
<td>-0.006%</td>
<td>0.369%</td>
</tr>
<tr>
<td>Seasonal TOU</td>
<td>-0.001%</td>
<td>0.394%</td>
</tr>
<tr>
<td>RTP</td>
<td>-0.013%</td>
<td>0.409%</td>
</tr>
</tbody>
</table>

The change in total yearly emissions, compared to the flat rate, under different market settings. To quantify the changes, we calculate the total emissions from electricity demand under the flat rate in 2010 as 21 Mtonnes of CO$_2$.

and the RTP in terms of the annual peak load reduction. However, seasonal TOU tariff and the RTP are better at reducing the Christmas peak load.

Under this setting, consumers’ electricity bills increase by less than 1% on average. The electricity bill increases at most by 3% for any household switching from a flat-rate to any time-based tariff. The distribution of change in annual electricity bills in this equilibrium setting is given in Figure EC.3. The slight increase in bills under this setting can be directly attributed to the increase in the total consumption.

Finally, the change in emissions under this setting are given in Table EC.7. We see that the increase in the total consumption under the time-based rates reflects to total emissions as well.

Appendix EC.6: Selection of Model Variables

Our demand equation is given by (3), and as discussed in Section 5, we modify the parameters of this equation using several variables as follows: We assume that each hour’s own price sensitivity parameter is given by $\beta_{dt}^n = \beta_0 + \beta_1 \text{monitor}^n + \beta_2 \text{peak}_t + \beta_3 \text{day}_t$. Here, monitor$^n$ indicates the presence of an electricity monitor in household $n$; peak, and day, are indicator variables that show the pricing period of hour $t$ in the experiment. Likewise, the intercept parameter is modeled as $\alpha_{dt}^n = \alpha_0 + \alpha_{\text{adults}}^n \text{num adults}^n + \alpha_{\text{temp}} \text{temp}_{dt} + \alpha \cdot \tilde{Z}_{dt}$. Here, num.adults$^n$ captures the number of adult occupants of household $n$ as a surrogate for the size of the home; temp$_{dt}$ denotes the
Figure EC.3  The change in annual consumer bills across all households, compared to the flat rate.

Note. On average, there is a reduction in bills for 20% of households under TOU tariffs, and for 35% under RTP. Under TOU tariffs, the increase in bills are less than 1% for half of the households, and less than 2% for 80% of the households. Under RTP, the increase in bills are less than 1% for 70% of the households, and less than 2% for 80% of the households. Annual average electricity bill is €870 per household.

Temperature (in Celsius) for day \(d\), hour \(t\); \(\tilde{Z}_{dt}\) includes the season and hour indicators for day \(d\) and hour \(t\).

For both \(\alpha_{dt}\) and \(\beta_{dt}\), we started with an exhaustive list of all relevant variables that are available to us, and selected our final variables from that list to strike a balance between more explanatory power and overfitting.

Potential variables that can have an effect on a households level of consumption \((\alpha_{dt})\) are the seasonality terms, and households demographic characteristics. Given that seasonality variables are easily observed by the retailer, and are identical for all households, we included all of the significant terms, which are the hourly temperature, hours of the day, and the seasons within the year (we did not find a significant difference in consumption between different weekdays). The household-specific variables that are available to us come from the telephone-assisted survey that the experiment households answered, which can be listed as:

- Demographic and household characteristics: Sex, age, employment status, income (intervals), internet access, number of adults and children living in the household, type of home ownership (rental/own), age of building, area, number of bedrooms.
- The frequency of use and ownership of the following appliances: Washing machine, tumble dryer, dishwasher, electric shower, electric cooker, electric heater, freezer, water pump, immersion heater, TV’s less than and greater than 21 inches, desktop and laptop computers, game consoles.
- Qualitative questions on general energy saving and electricity use habits, insulation and use of energy saving lightning, expectations from participating in the trial, and satisfaction from the current electricity market in terms of costs, level of competition and emissions.

We took the benchmark period consumption data (no pricing treatment), and compared the explanatory power added by each of these variables via a stepwise-analysis. Our results indicate that the most significant variables that explain the consumption are (in order of additional explanatory power gained in the first step): Number of adults in the household, number of children in the household, number of bedrooms, number of desktop computers and large TVs, the use frequency of dishwashers, immersion heaters, electric cookers, and the dryers. We have found that the number
of adults variable is correlated with the other significant variables in the list, and when included by itself, covers above half of the variation that is eliminated when all of these variables are included.

For the price-sensitivity terms, the only seasonality terms we can identify are the peak, day, and night pricing periods and we include these (pricing in the experiment data does not differ by hours of the day, or seasons in the year). We exclude household-specific demographic variables from the price-sensitivity parameters for model relevance, because retailers are not allowed to price-discriminate between customers based on their demographic characteristics, and they also might not be able to fully observe such characteristics. Therefore, the retailer is only interested in the populations average price response when setting the prices (even if they know for example that more crowded households are more price-sensitive, they would have to make their pricing decisions based on the average households size). We acknowledge that while it might be interesting to learn how the household demographics affect price sensitivity; it is beyond the scope of our paper.

Finally, only a subset of households were equipped with an electricity monitor, and we included an indicator for the presence of it because it increases the price sensitivity of households significantly, and it can be relevant to a retailer decide whether to roll-out such informative displays. The electricity monitor is randomly distributed and has no significant effect on the households overall consumption level, and is therefore omitted from $\alpha_{dt}^n$. 